you can apply a similar approach to portfolio management in the context of Nepal. Here are some steps and considerations to adapt the methodology:

**1. Identify Local Market Indices and ETFs**

* **Nepal Stock Exchange (Nepse)**: Look for ETFs or indices that track the Nepse. While ETFs are not as common in Nepal as in the US, you can still find mutual funds or other investment vehicles that track the Nepse index.
* **Bond Indices**: Identify any available bond indices or funds that invest in Nepalese government or corporate bonds.
* **Commodity Indices**: While there might not be a direct commodity index for Nepal, you can consider global commodity ETFs that are relevant to the Nepalese economy.
* **Volatility Index**: If a local volatility index is not available, you might need to rely on global volatility indices or create a proxy using local market data.

**2. Data Gathering**

* **Historical Data**: Collect historical price data for the identified indices or funds. This can be sourced from Nepse, financial news websites, or financial data providers.
* **Correlation Analysis**: Perform rolling correlation analysis to understand the relationships between different asset classes in Nepal. This will help in diversification.

1. **AdvancedNEPSE** by Pukar99:
   * This project focuses on conducting thorough Exploratory Data Analysis (EDA) and developing predictive models for the Nepalese stock market. [It includes the implementation of a Long Short-Term Memory (LSTM) model to predict future stock prices based on historical data1](https://github.com/Pukar99/AdvancedNEPSE).
   * [GitHub Repository](https://github.com/Pukar99/AdvancedNEPSE)
2. **nepstonks** by sarojbelbase:
   * An automated bot that scrapes the latest upcoming issues, news, and investment opportunities announced in Nepal and sends them to a Telegram channel. [This project is useful for staying updated with the latest market trends2](https://github.com/topics/nepse).
   * GitHub Repository
3. **nepseutils** by arpandaze:
   * A CLI application to automatically apply for IPOs in MeroShare. [This tool can be handy for investors looking to streamline their IPO application process2](https://github.com/topics/nepse).
   * GitHub Repository

LSTM VS TR

In the context of **portfolio management**, both LSTM and Transformer models have their advantages, depending on the complexity of the data, objectives of the model, and available resources. Let’s break down how each model can be applied in portfolio management and which one might be more suitable.

**1. Modeling Time Series Data**

* **LSTM**:
  + **Strengths**: LSTMs are naturally suited for sequential, time series data like stock prices, bond yields, or other financial metrics. They can capture short-term trends in asset prices, volatilities, and other financial indicators.
  + **Use Case**: LSTMs might be well-suited for **short-term forecasting** in portfolio management, where the focus is on capturing short-term price movements, volatility shifts, or market momentum.
* **Transformers**:
  + **Strengths**: Transformers, due to their self-attention mechanism, can effectively handle **long-term dependencies** in financial data. In portfolio management, this can mean understanding how long-term macroeconomic factors or correlations between different assets evolve over time.
  + **Use Case**: Transformers could be ideal for **long-term portfolio management** strategies, where capturing broader trends, market regimes, or complex dependencies between multiple asset classes is critical.

**Verdict**: If you're focusing on **short-term price movements** and **daily portfolio rebalancing**, LSTMs could be better. For more **long-term portfolio strategies**, where the model needs to consider multiple financial variables over time, Transformers may be more effective.

**2. Modeling Multivariate Financial Data**

* **LSTM**:
  + LSTMs can handle multivariate data, but they typically do so sequentially. If you're looking to include a lot of factors (e.g., prices, volumes, macroeconomic indicators) that interact over time, LSTMs may struggle with capturing all of these relationships simultaneously, especially over long sequences.
* **Transformers**:
  + Transformers are well-suited for **multivariate time series data** because they can handle dependencies between multiple financial variables (e.g., stocks, bonds, commodities) over time. Self-attention allows each element in the series (such as different asset classes or macro indicators) to attend to every other element, making it easier to understand interactions between assets.

**Verdict**: For complex portfolios involving **multiple assets** or factors (e.g., multi-asset portfolio management, factor investing), **Transformers** will generally provide better performance.

**3. Handling Long-Term Dependencies and Regime Changes**

* **LSTM**:
  + LSTMs can model dependencies between variables, but their performance degrades when the sequence becomes too long (i.e., when considering long periods of historical data). They may fail to capture regime changes (e.g., bull vs. bear markets) effectively due to their limited memory and focus on recent data.
* **Transformers**:
  + Transformers excel at **capturing long-term dependencies** and can detect regime changes in markets by learning patterns from data over extended periods. For example, they can recognize shifts in volatility or correlations across assets, which is crucial for risk management and rebalancing portfolios during periods of market stress.

**Verdict**: For strategies that require **long-term trend detection** and regime shifts (e.g., in risk parity or asset allocation), **Transformers** are the better choice.

**4. Scalability and Portfolio Complexity**

* **LSTM**:
  + LSTMs are more resource-efficient for small portfolios or scenarios where the number of assets or features being tracked is relatively low. However, as the number of assets increases, or if the strategy involves high-frequency trading, LSTMs may struggle to scale.
* **Transformers**:
  + **Scalability** is a key strength of Transformers. They can handle large datasets, process a large number of assets simultaneously, and efficiently model interactions between them. This is especially useful for managing large portfolios involving hundreds or even thousands of assets, as well as for high-frequency strategies.

**Verdict**: **Transformers** are generally better for large, complex portfolios and high-dimensional datasets.

**5. Interpretability and Feature Importance**

* **LSTM**:
  + LSTMs can be harder to interpret, as they rely on hidden states that evolve over time. While it’s possible to track which features influence the model, it can be difficult to pinpoint exactly how different factors are impacting portfolio decisions.
* **Transformers**:
  + Transformers’ **self-attention** mechanism makes it easier to understand which features (e.g., specific assets, macroeconomic indicators, or time periods) are most important for the model’s decisions. This transparency can be valuable in portfolio management, where understanding the drivers of risk and return is crucial.

**Verdict**: **Transformers** provide more transparency and interpretability in terms of understanding feature importance, making them a better fit when the strategy requires explainability.

**6. Risk Management**

* **LSTM**:
  + LSTMs can model individual asset price trends, but they may not capture complex, evolving correlations between assets that drive portfolio-level risks. This could be limiting for sophisticated risk management strategies.
* **Transformers**:
  + Transformers can effectively model correlations and **changing relationships between assets**, making them better suited for risk management. By understanding how asset prices are influenced by each other (e.g., in a multi-asset portfolio), Transformers can help in dynamically adjusting portfolio risk profiles.

**Verdict**: For advanced **risk management** (especially in multi-asset portfolios), **Transformers** are more robust.

**7. Market Sentiment and External Data Integration**

* **LSTM**:
  + LSTMs can integrate external data, like news or social sentiment, but they may struggle with large unstructured datasets, especially when the data is textual in nature (e.g., news headlines or social media sentiment).
* **Transformers**:
  + Transformers, especially language models (like BERT or GPT), excel at integrating external data such as **financial news**, social media sentiment, or analyst reports. This can provide valuable insights for portfolio management by analyzing sentiment data to predict how the market might react to certain events.

**Verdict**: **Transformers** are better suited for integrating external data and analyzing sentiment for **sentiment-driven trading strategies** or **event-driven portfolio adjustments**.

**Conclusion:**

In the context of portfolio management, **Transformers generally outperform LSTMs**, especially for:

* **Long-term portfolio strategies** where capturing broad trends and market regime changes is essential.
* **Large, complex portfolios** involving multiple assets and factors.
* **Risk management** where dynamic relationships between assets need to be modeled.
* **Incorporating external data** like news, sentiment, or macroeconomic factors.

However, **LSTMs** may still be a good choice for simpler, **short-term** strategies, especially when resources are limited or the focus is on individual asset price prediction in a small portfolio.