**Literature Survey**

Our research builds upon advancements in time series forecasting, focusing on ARIMA models, LSTM networks, and hybrid approaches. These methods address key challenges in short-term temperature prediction, providing insights into their strengths, limitations, and suitability for practical applications.

**ARIMA: Strength in Linear Forecasting**

ARIMA models excel in capturing linear trends and seasonal patterns in time series data. Murat et al. (2018) demonstrated ARIMA's robustness in forecasting daily meteorological data, achieving a mean absolute percentage error (MAPE) of 3.2% for temperature predictions. These results position ARIMA as an effective baseline model for analyzing trends and seasonality in weather data.

However, Ye et al. (2018) highlighted ARIMA's limitations in handling non-linear and chaotic variations, which often characterize weather data. While ARIMA performs well for short-term forecasts, its accuracy diminishes for longer-term predictions or datasets with non-linear dependencies. These limitations justify the integration of more advanced models, such as LSTM, to address non-linear patterns.

**LSTM: Strength in Non-linear Dependencies**

LSTM models have proven highly effective in capturing complex, non-linear patterns in time series data. Siami-Namini et al. (2018) reported an 84-87% reduction in RMSE when using LSTM over ARIMA for non-linear datasets, highlighting LSTM's potential for improved forecast accuracy. De Saa & Ranathunga (2021) further validated LSTM's effectiveness in scenarios involving rapid temperature changes, achieving a 15% lower RMSE compared to ARIMA.

Despite their advantages, LSTM models are computationally intensive and prone to overfitting on small datasets. To address these challenges, our project incorporates robust preprocessing, hyperparameter tuning, and dropout regularization. This ensures LSTM's strengths are maximized while mitigating its limitations in short-term temperature prediction.

**Hybrid Approaches: Combining ARIMA and LSTM**

Hybrid ARIMA-LSTM models leverage the respective strengths of both approaches to improve forecasting accuracy. Salman et al. (2018) demonstrated a 20% reduction in RMSE with a hybrid model compared to standalone ARIMA and a 10% reduction compared to LSTM. Abdallah et al. (2020) reinforced these findings, showcasing a 25% improvement in short-term temperature predictions using a hybrid methodology.

While hybrid models address many limitations of standalone approaches, challenges remain, such as increased computational complexity and scalability. Our project addresses these by optimizing hybrid configurations and validating the model's performance across diverse U.S. climate patterns. These efforts aim to develop a generalizable and efficient forecasting framework.

**Research Gaps and Our Contributions**

Existing research highlights gaps in hybrid model scalability, generalizability, and comparative evaluation across traditional and deep learning methods. Few studies explore how hybrid ARIMA-LSTM models perform across different geographical regions and climate conditions, limiting their real-world applicability.

To address these gaps, our project tests hybrid ARIMA-LSTM models on a diverse set of U.S. cities, ensuring scalability and efficiency with large datasets. By providing a detailed comparative analysis of ARIMA, LSTM, and hybrid models, we aim to advance forecasting techniques and contribute actionable insights for industries reliant on accurate temperature predictions.