f-bayesian-CNN-LSTM-Q-learning

March 4, 2024

1 Predicting Implicit Patterns and Optimizing Market Entry and Exit Decisions in Stock Prices using integrated Bayesian CNN-LSTM with Deep Q-Learning as a Meta-Labelle

We are doing the following in this project

- Train a Bayesian CNN-LSTM hybrid to predict the stock returns
- In the process estimate the uncertianty of the Bayesian CNN-LSTM prediction
- Use the Bayesian CNN–LSTM prediction and the uncertainty estimations as states to train Deep Q-learning agent (DQA).
- The purpose of training the DQA is to determine the size of bet based on Bayesian CNN-LSTM prediction and the uncertainty of the prediction of the Bayesian CNN-LSTM prediction

[1]:
```
import datetime
import math

import numpy as np
import pandas_datareader.data as web
import seaborn as sns
import yfinance as yf
import pandas as pd
import matplotlib.pyplot as plt
from scipy.stats import boxcox,probplot,shapiro
# from sklearn_fracdiff import FracDiff
from sklearn.model_selection import train_test_split
from pyts.image import GramianAngularField
from keras.models import Sequential
from keras.layers import Conv1D,Bidirectional, MaxPooling1D, Flatten,␣
↪Dense,Reshape,LSTM,Dropout,TimeDistributed
from sklearn.metrics import mean_squared_error
from sklearn.neural_network import MLPRegressor
from keras.optimizers import Adam
from keras import backend as keras_b
import tensorflow as tf
from keras.models import load_model
from sklearn.model_selection import ParameterGrid
import random
from collections import deque
```

```
import pickle
import warnings
warnings.filterwarnings('ignore')
plt.rcParams["figure.figsize"] = (16, 9)
```

```
WARNING:tensorflow:From D:\sagan\financial engineering\courses\Capstone
project\submissions\codes\.envs\lib\site-packages\keras\src\losses.py:2976: The
name tf.losses.sparse_softmax_cross_entropy is deprecated. Please use
tf.compat.v1.losses.sparse_softmax_cross_entropy instead.
```

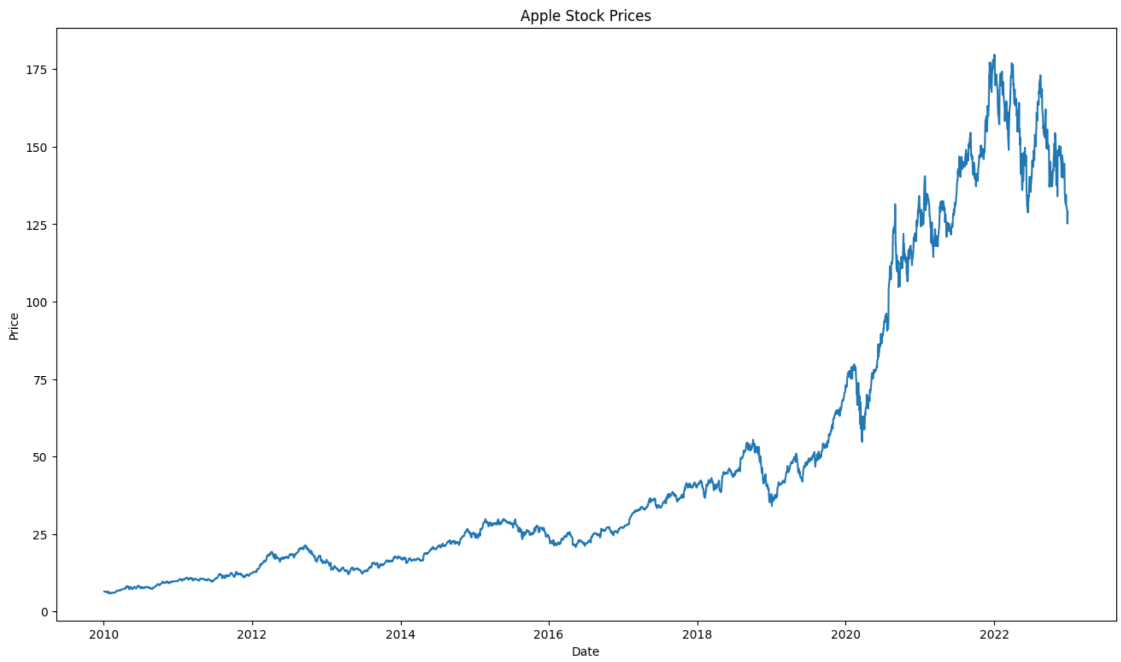
2 1. DATA COLLECTION FOR TRAINING & TESTING

We will collect APPLE Stocks from 2005-01-01 to 2021-12-21

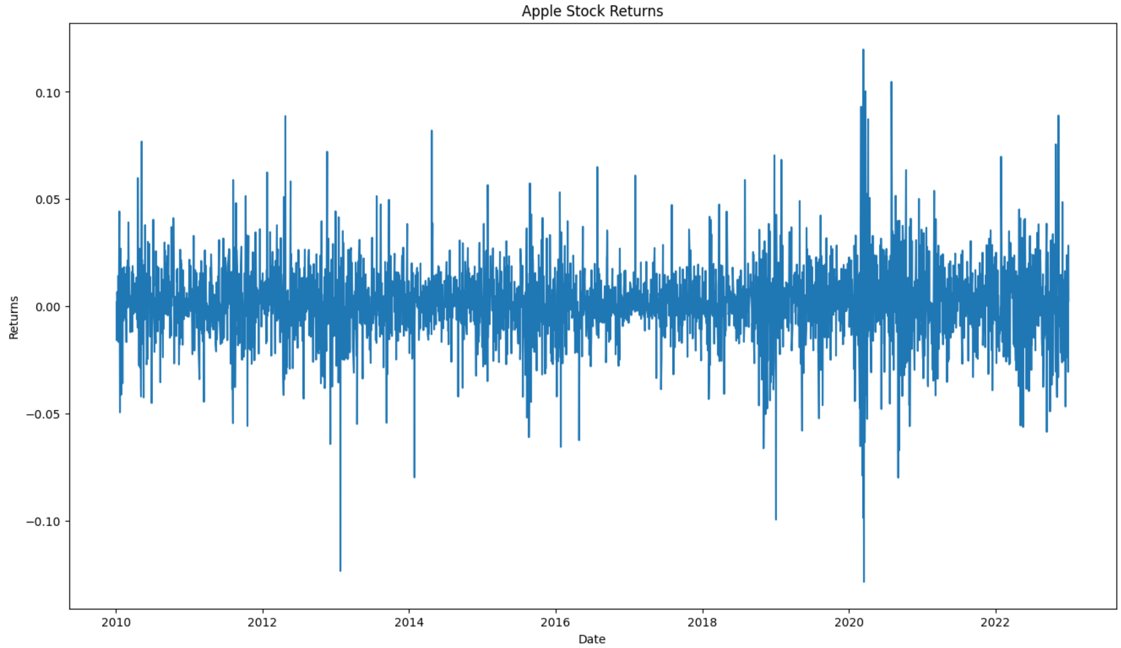
[2]:
```
# Defined start and end dates for the data
start_date = '2010-01-01'
end_date = '2022-12-31'

# Fetch the data using the Yahoo Finance API
apple_data = yf.download('AAPL', start=start_date, end=end_date)
# Display the first few rows of the data
print(apple_data.head())
apple_data.to_csv("apple_stock_prices.csv")
```

```
[*********************100%%**********************]  1 of 1 completed

                Open      High       Low     Close  Adj Close     Volume
Date
2010-01-04  7.622500  7.660714  7.585000  7.643214   6.470740  493729600
2010-01-05  7.664286  7.699643  7.616071  7.656429   6.481929  601904800
2010-01-06  7.656429  7.686786  7.526786  7.534643   6.378828  552160000
2010-01-07  7.562500  7.571429  7.466071  7.520714   6.367032  477131200
2010-01-08  7.510714  7.571429  7.466429  7.570714   6.409362  447610800
```

[2]:
```
# Load the data from the CSV file
data = pd.read_csv("apple_stock_prices.csv")

# Convert the 'Date' column to datetime format
data["Date"] = pd.to_datetime(data["Date"])

# Create the line plot
plt.plot(data["Date"], data["Adj Close"])
plt.title("Apple Stock Prices")
plt.xlabel("Date")
plt.ylabel("Price")
plt.show()
```



[3]:
```
# Calculate the returns
data['Returns'] = data['Adj Close'].pct_change()


# Drop rows with missing values (NaNs) resulting from the shifting
data.dropna(inplace=True)
# Create the line plot
plt.plot(data["Date"], data["Returns"])
plt.title("Apple Stock Returns")
plt.xlabel("Date")
plt.ylabel("Returns")
plt.show()
```



[5]:
```
data.head()
```

[5]:
```
         Date      Open      High       Low     Close  Adj Close     Volume  \
1  2010-01-05  7.664286  7.699643  7.616071  7.656429   6.481929  601904800
2  2010-01-06  7.656429  7.686786  7.526786  7.534643   6.378828  552160000
3  2010-01-07  7.562500  7.571429  7.466071  7.520714   6.367032  477131200
4  2010-01-08  7.510714  7.571429  7.466429  7.570714   6.409362  447610800
5  2010-01-11  7.600000  7.607143  7.444643  7.503929   6.352821  462229600

    Returns
1  0.001729
2 -0.015906
3 -0.001849
4  0.006648
5 -0.008822
```

3 2 Reprocess the return

- For each window of 100 consecutive data points,`X[i]`, the percentage change δx_i is calculated relative to the first data point in the window. This is represented by:

$$\delta x_i = \frac{x_{100+i} - x_i}{x_i}$$

where x_{100+i} is the value at the end of the window (i.e., the 100th data point), and x_i is the value at the start of the window (i.e., the 1st data point).

- For the corresponding target value, `Y[i]`, the percentage change δy_i is calculated as the difference between the value at the next time step (i.e., x_{101+i}) and the value at the start of the window (i.e., x_i), divided by the value at the start of the window. This is represented by:

$$\delta y_i = \frac{x_{101+i} - x_i}{x_i}$$

Consequently, `X[i]` represents the percentage change within the window, and `Y[i]` represents the percentage change at the next time step after the window.

[4]:
```
X = []
Y = []
window_size=100
for i in range(1 , len(data) - window_size -1 , 1):
    first = data.iloc[i,5]
    # print(first)
    temp = []
    temp2 = []
    for j in range(window_size):
        temp.append((data.iloc[i + j, 5] - first) / first)
    temp2.append((data.iloc[i + window_size, 5] - first) / first)
    X.append(np.array(temp).reshape(100, 1))
    Y.append(np.array(temp2).reshape(1, 1))
# Split the data into training, validation, and testing sets
X_train_val, X_test_, y_train_val, y_test_ = train_test_split(
    X, Y, test_size=0.2, shuffle=True
)

# # Further split the training set into training and validation sets
X_train_, X_val_, y_train_, y_val_ = train_test_split(
    X_train_val,
    y_train_val,
    test_size=0.2,
    shuffle=True
)

X_train = np.array(X_train_)
X_test = np.array(X_test_)
X_val = np.array(X_val_)
y_train = np.array(y_train_)
y_val = np.array(y_val_)
y_test = np.array(y_test_)
# # Reshape the input data for CNN (channels last)
X_train = X_train.reshape(X_train.shape[0],1,100,1)
X_val = X_val.reshape(X_val.shape[0],1,100,1)
X_test = X_test.reshape(X_test.shape[0],1,100,1)

print(len(X_train))
```

```
print(len(X_val))
print(len(X_test))
```

```
2028
507
634
```

[7]:
```
# y_test
```

[8]:
```
len(X)
```

[8]:
```
3169
```

4 3. Training the Bayesian CNN-LSTM

Combining Monte Carlo Dropout (MC Dropout) with a Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) network involves extending the MC Dropout methodology to both the CNN and LSTM components. Below are the steps to incorporate MC Dropout into a hybrid Bayesian CNN-LSTM model:

1. **Modify the CNN-LSTM Architecture:**
   - Introduce dropout layers after convolutional layers in the CNN part and after the LSTM layers in the LSTM part of your architecture.

[9]:
```
# For creating model and training
model_bay_cnn_lstm = Sequential()

# Creating the Neural Network model here...
# CNN layers
model_bay_cnn_lstm.add(
    TimeDistributed(
        Conv1D(64, kernel_size=3, activation='relu', input_shape=(None, 1,100,␣
 ↪1)
               )
    )
)
model_bay_cnn_lstm.add(
    TimeDistributed(
        Dropout(0.25)
    )
)
model_bay_cnn_lstm.add(
    TimeDistributed(
        MaxPooling1D(2)
    )
)
model_bay_cnn_lstm.add(
    TimeDistributed(
```

```python
        Conv1D(128, kernel_size=3, activation='relu')
    )
)
model_bay_cnn_lstm.add(
    TimeDistributed(
        MaxPooling1D(2)
    )
)
model_bay_cnn_lstm.add(
    TimeDistributed(
        Conv1D(64, kernel_size=3, activation='relu')
    )
)
model_bay_cnn_lstm.add(TimeDistributed(MaxPooling1D(2)))
model_bay_cnn_lstm.add(TimeDistributed(Flatten()))

# LSTM layers
model_bay_cnn_lstm.add(Bidirectional(LSTM(100, return_sequences=True)))
model_bay_cnn_lstm.add(Bidirectional(LSTM(100, return_sequences=False)))
model_bay_cnn_lstm.add(Dropout(0.5))

#Final layers
model_bay_cnn_lstm.add(Dense(1, activation='linear'))
model_bay_cnn_lstm.compile(optimizer='adam', loss='mse', metrics=['mse', 'mae'])
```

```
WARNING:tensorflow:From D:\sagan\financial engineering\courses\Capstone
project\submissions\codes\.envs\lib\site-packages\keras\src\backend.py:873: The
name tf.get_default_graph is deprecated. Please use
tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From D:\sagan\financial engineering\courses\Capstone
project\submissions\codes\.envs\lib\site-
packages\keras\src\optimizers\__init__.py:309: The name tf.train.Optimizer is
deprecated. Please use tf.compat.v1.train.Optimizer instead.
```

2. **Enable Dropout During Inference:**

To perform MC Dropout during inference, we need to manually enable dropout at test time. This involves setting the training parameter of the model to True during inference. This step is crucial for obtaining multiple predictions with varying dropout masks..

[13]:
```python
def enable_dropout(model_bay_cnn_lstm):
    for layer in model_bay_cnn_lstm.layers:
        if isinstance(layer, (Dropout, LSTM, TimeDistributed)):
            layer.training = True
```

3. **Training:** We train the model as we would with a standard CNN, but with the dropout layers included. The dropout layers are automatically active during training.

[11]:
```
# # Train the model

history = model_bay_cnn_lstm.fit(
    X_train, y_train,
    batch_size=32,
    epochs=20,
    validation_data=(X_val, y_val),
    verbose=0
)
```

```
WARNING:tensorflow:From D:\sagan\financial engineering\courses\Capstone
project\submissions\codes\.envs\lib\site-packages\keras\src\backend.py:6642: The
name tf.nn.max_pool is deprecated. Please use tf.nn.max_pool2d instead.

WARNING:tensorflow:From D:\sagan\financial engineering\courses\Capstone
project\submissions\codes\.envs\lib\site-
packages\keras\src\utils\tf_utils.py:492: The name tf.ragged.RaggedTensorValue
is deprecated. Please use tf.compat.v1.ragged.RaggedTensorValue instead.

WARNING:tensorflow:From D:\sagan\financial engineering\courses\Capstone
project\submissions\codes\.envs\lib\site-
packages\keras\src\engine\base_layer_utils.py:384: The name
tf.executing_eagerly_outside_functions is deprecated. Please use
tf.compat.v1.executing_eagerly_outside_functions instead.
```

4. **Perform Multiple Predictions:**
    - When making predictions,we enable dropout during inference, and make multiple predictions to capture uncertainty.

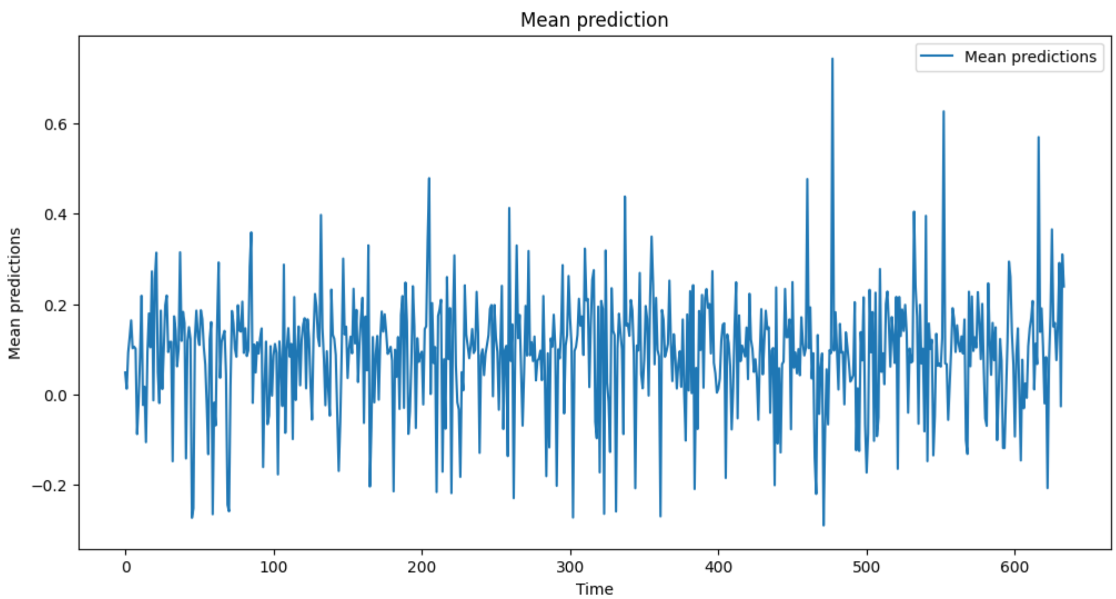
[12]:
```
num_predictions = 100
predictions = []

for _ in range(num_predictions):
    enable_dropout(model_bay_cnn_lstm)
    pred = model_bay_cnn_lstm.predict(X_test,verbose=0)  # x_test is your test␣
 ↪data
    predictions.append(pred)

predictions = np.array(predictions)
```

5. **Aggregating Predictions:**

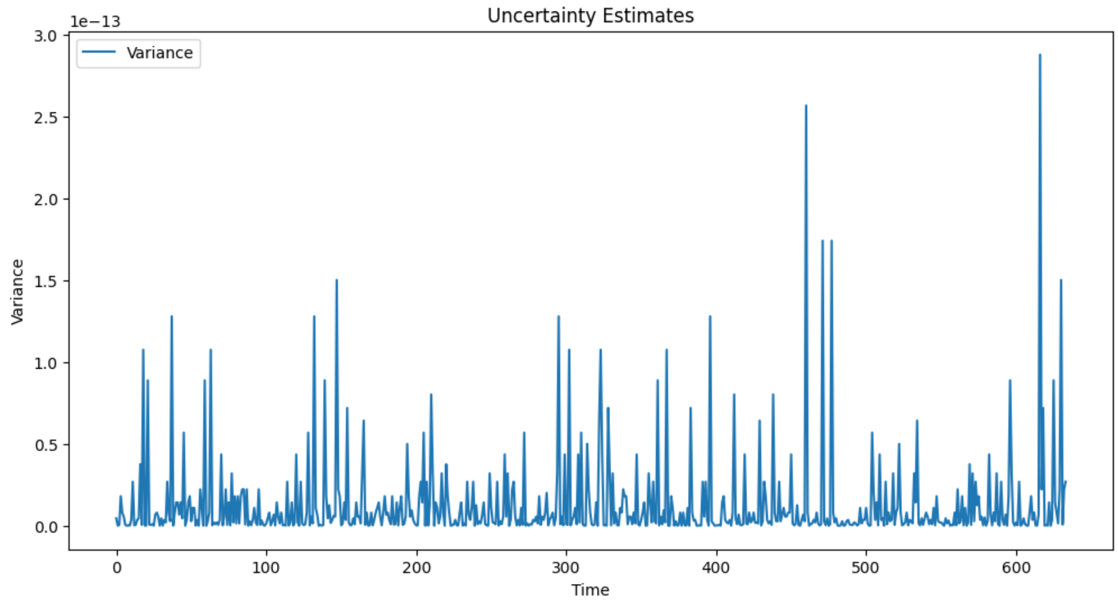
We aggregate the predictions to obtain a measure of uncertainty. We shall use the mean or variance of the predictions as aggregation method. The mean prediction provides an estimate of the point prediction, while the variance can be considered a measure of uncertainty..

[13]:
```
mean_prediction = np.mean(predictions, axis=0)
uncertainty = np.var(predictions, axis=0)
```

[14]:
```python
# uncertainty
plt.figure(figsize=(12, 6))
plt.plot(mean_prediction, label='Mean predictions')
plt.xlabel('Time')
plt.ylabel('Mean predictions')
plt.title('Mean prediction')
plt.legend()
plt.show()
```



[15]:
```python
# uncertainty
plt.figure(figsize=(12, 6))
plt.plot(uncertainty, label='Variance')
plt.xlabel('Time')
plt.ylabel('Variance')
plt.title('Uncertainty Estimates')
plt.legend()
plt.show()
```



[ ]:

```

```

Save the Bayesian CNN-LSTM model

[16]:

```
# Save the model architecture as JSON
model_bay_cnn_lstm_json = model_bay_cnn_lstm.to_json()
with open("model_architecture.json", "w") as json_file:
    json_file.write(model_bay_cnn_lstm_json)

# Save the model weights
model_bay_cnn_lstm.save_weights("trained_bayesian_CNN_LSTM_weights.h5")

# Optionally, saving the entire model (including architecture and weights) in a␣
 ↪single .h5 file
model_bay_cnn_lstm.save("complete_bayesian_cnn_lstm.h5")

# model_bay_cnn_lstm.save_weights('trained_bayesian_CNN_LSTM_weights.h5')
```

[77]:

```
# Load the saved model
loaded_bay_cnn_lstm_model = load_model('complete_bayesian_cnn_lstm.h5')
```

[78]:

```
# # Evaluate the model on the validation and test sets
val_loss = loaded_bay_cnn_lstm_model.evaluate(X_val, y_val)
test_loss = loaded_bay_cnn_lstm_model.evaluate(X_test, y_test)
print("Validation loss:", val_loss)
print("Test loss:", test_loss)
```

```
# Make predictions
y_pred = loaded_bay_cnn_lstm_model.predict(X_test)
```

```
16/16 [==============================] - 4s 15ms/step - loss: 0.0051 - mse:
0.0051 - mae: 0.0547
20/20 [==============================] - 0s 17ms/step - loss: 0.0049 - mse:
0.0049 - mae: 0.0533
Validation loss: [0.005087577272206545, 0.005087577272206545,
0.054742660373449326]
Test loss: [0.0049483939073979855, 0.0049483939073979855, 0.05327653884887695]
20/20 [==============================] - 3s 13ms/step
```

[18]:
```
X_test.shape
```

[18]: (634, 1, 100, 1)

[19]:
```
y_pred.shape
```

[19]: (634, 1)

[176]:
```
y_test_list=[]
for i in y_test:
    y_test_list.append(i)
```

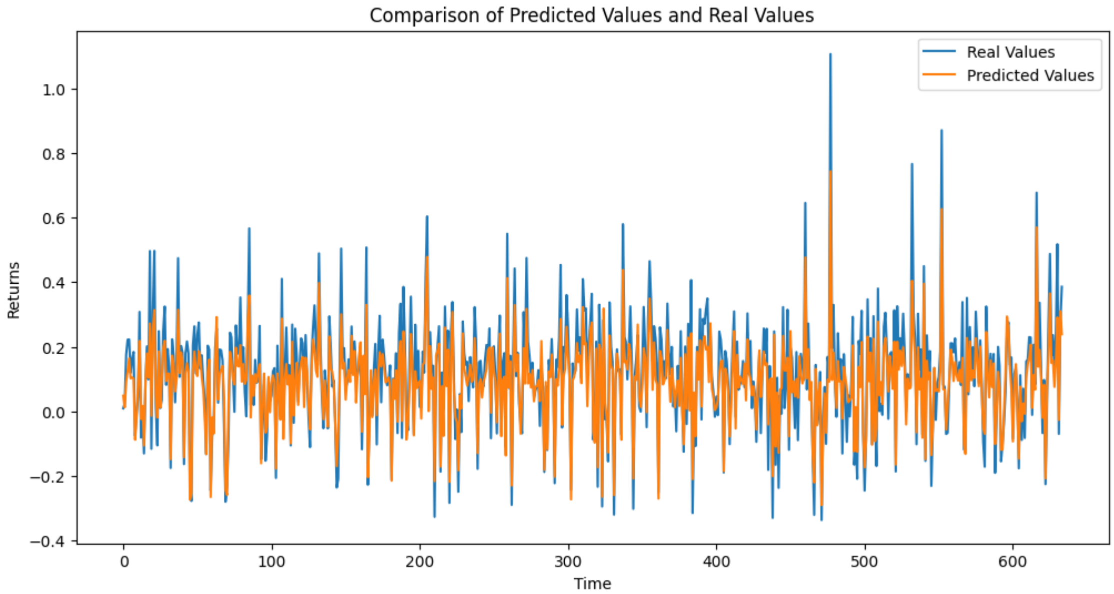
[177]:
```
data2=pd.DataFrame(y_pred,columns=["pred"])
data2["real"]=y_test_list
```

[22]:
```
# y_test
```

[23]:
```
# data2.head(10)
```

[24]:
```
# Plot the graph comparing predicted values and real values
y_pred = model_bay_cnn_lstm.predict(X_test)

plt.figure(figsize=(12, 6))
plt.plot(data2['real'], label='Real Values')
plt.plot(data2['pred'], label='Predicted Values')
plt.xlabel('Time')
plt.ylabel('Returns')
plt.title('Comparison of Predicted Values and Real Values')
plt.legend()
plt.show()
```

```
20/20 [==============================] - 0s 12ms/step
```



5 5.Market Timing with Deep Q-learning

5.1 Rescale Uncertainty

Since the uncertainty estimates are those of percentage returns, the uncertainty as seen from above are of a very smaller scale ($1e-13$), to make the uncertainty penalty to have effect in agent's learning, we are going to scale the uncertainty

[ ]:
```
# Function to get states from your Bayesian CNN-LSTM model and incorporate␣
↪uncertainty
def get_states():
    # create an extended state that incorporated uncertainty estimation
    # and the predictions
    # We limit the state size to 100*2
    # This is necessary to maintain consistency
    extended_state = np.concatenate((y_pred[:100,:], uncertainty[:100,:]),␣
↪axis=1)
    return extended_state
```

[5]:
```
# The DQN agent
class DQNAgent:
    def __init__(self, state_size, action_size,uncertainty_penalty):
        self.state_size = state_size
        self.action_size = action_size
        self.memory = deque(maxlen=200)  # Experience replay buffer
        self.gamma = 0.95  # Discount factor
        self.epsilon = 1.0  # Exploration-exploitation trade-off
```

```
        self.epsilon_decay = 0.995
        self.epsilon_min = 0.01
        self.learning_rate = 0.001
        self.uncertainty_penalty=uncertainty_penalty
        self.model = self._build_model()

    def _huber_loss(self,y_true, y_pred, clip_delta=1.0):
        error = y_true - y_pred
        cond  = keras_b.abs(error) <= clip_delta

        squared_loss = 0.5 * keras_b.square(error)
        quadratic_loss = (
                    0.5 * keras_b.square(clip_delta) +
                    clip_delta * (keras_b.abs(error) - clip_delta)
                )

        return keras_b.mean(tf.where(cond, squared_loss, quadratic_loss))

    def _build_model(self):
        model = Sequential()
        model.add(Flatten(input_shape=(state_size, 2)))  # Flatten layer to␣
↪reshape input
        model.add(Dense(24, activation='relu'))
        model.add(Dense(24, activation='relu'))
        model.add(Dense(self.action_size, activation='linear'))
        model.compile(
            loss=self._huber_loss,
            optimizer=Adam(learning_rate=self.learning_rate)
        )
        # model = Sequential()
        # model.add(Dense(24, activation='relu'))
        # model.add(Dense(24, activation='relu'))
        # model.add(Dense(self.action_size, activation='linear'))
        # model.compile(loss='mse', optimizer=Adam(learning_rate=self.
↪learning_rate))
        return model

    def remember(self, state, action, reward, next_state, done):
        # print(state.shape)
        self.memory.append((state, action, reward, next_state, done))

    def act(self, state,current_holding=0):
        if np.random.rand() <= self.epsilon:
            # Randomly select action from the action space: short, do nothing,␣
↪long
            return np.random.uniform(-1, 1)
        else:
```

```
            # Use the Q-network to select action based on state
            return np.argmax(self.model.predict(state,verbose=0)[0])

    def replay(self, batch_size):
        minibatch = random.sample(self.memory, batch_size)
        for state, action, reward, next_state, done in minibatch:
            target = reward
            # print(next_state.shape)
            if not done:
                # print(self.model.predict(next_state))
                target = reward + self.gamma * np.amax(self.model.
 ↪predict(next_state,verbose=0)[0])
            # print(state.shape)
            target_f = self.model.predict(state,verbose=0)
            # print(action)
            target_f[0][0] = target
            self.model.fit(state, target_f, epochs=1, verbose=0)
        if self.epsilon > self.epsilon_min:
            self.epsilon *= self.epsilon_decay

# The Market environment
class MarketEnvironment:
    def __init__(self,agent, max_episode_length=100, min_available_capital=10,␣
 ↪max_trades=None, profit_target=None, stop_loss=-5000):
        self.state_size = state_size  # The actual size of your state
        self.action_size = 1  # Example: Buy, Sell, Hold
        self.initial_capital = 10000  # Initial available capital
        self.transaction_cost = 0.01  # Transaction charge (1%)
        self.current_capital = self.initial_capital
        self.max_episode_length = max_episode_length
        self.min_available_capital = min_available_capital
        self.max_trades = max_trades
        self.profit_target = profit_target
        self.stop_loss = stop_loss
        self.num_trades = 0
        self.total_reward = 0
        self.uncertainty_penalty=agent.uncertainty_penalty

    def reset(self):
        # Reset logic
        self.current_capital = self.initial_capital
        self.num_trades = 0
        self.total_reward = 0
        # print(self.state_size)
        return np.random.rand(self.state_size)

    def step(self, action,time_state):
```

```
        # Extract market returns and uncertainty from the state
        market_returns = time_state[0]  # First column contains predicted␣
↪market returns
        uncertainty = time_state[1]     # Second column contains uncertainty␣
↪estimations
        # Simulated step function, returns next_state, reward, done
        next_state = np.random.rand(self.state_size,2)

        # Calculate bet size based on the selected action
        bet_size = abs(action) * self.current_capital

        # Calculate transaction cost based on the bet size
        total_transaction_cost=self.transaction_cost * bet_size
        # Subtract the transaction cost
        self.current_capital -= total_transaction_cost
        # Calculate the return based on the market return and the direction of␣
↪the trade
        # For a long position, return is market return * bet size
        # For not taking any position, return is 0
        if action > 0:
            return_direction = 1
        elif action<0:
            return_direction = -1
        else:
            return_direction = 0
        return_amount = return_direction * market_returns * bet_size
        yield_size=return_amount+bet_size
        if action > 0:
            # Adjust available capital based on bet size
            self.current_capital += return_amount

        # If action == 0, it means the agent wants to close the position
        elif action == 0:
            # Adjust available capital based on the current holding
            self.current_capital += return_amount
        # Calculate reward based on market return, transaction charges, and␣
↪uncertainty
        reward = return_amount
        #Since the uncertainty is calculated from return predictions,
        # The corresponding estimates take lower scales .i.e 1e-13
        # We have to scale this so that it can have effect on the reward
        # We scale by multiplying the uncertainty by 1e-11
        reward -= self.uncertainty_penalty * uncertainty*return_amount*1e-11
        # Increment total reward
        self.total_reward += reward

        # Increment number of trades
```

```
        self.num_trades += 1
         # Check termination conditions
        done = False
        if self.num_trades >= self.max_episode_length:
            done = True
        elif self.current_capital <= self.min_available_capital:
            done = True
        elif self.max_trades is not None and self.num_trades >= self.max_trades:
            done = True
        elif self.profit_target is not None and self.total_reward >= self.
 ↪profit_target:
            done = True
        elif self.stop_loss is not None and self.total_reward <= self.stop_loss:
            done = True
        return next_state, reward, done
```

[49]:
```
# EPISODE LENGTH
# This is equivalent to the time steps we would want our agent to master
EPISODE_LENGTH=15
EPISODES=10
```

Uncertainty penalty hyperparameter tuning

[50]:
```
# Hyperparameters
states=get_states()
state_size = states.size # The actual size of your state
print(state_size)
state_size=int(state_size/2) #The halfed state size for the input size
print(state_size)
action_size = 1  # Percentage defined as a ratio
batch_size = 32

# Define the uncertainty penalty range
param_grid = {'uncertainty_penalty': [0.9, 0.75, 0.5, 0.3, 0.1]}

best_score = -float('inf')
best_params = None

for params in ParameterGrid(param_grid):
    # Create the environment and agent
    agent = DQNAgent(state_size, action_size,params['uncertainty_penalty'])
    env = MarketEnvironment(agent)
    total_rewards = []
    # Training the DQN agent
    for episode in range(EPISODES):  # Replace with the desired number of␣
 ↪episodes
        state = env.reset()
```

```
        state_from_cnn_lstm = get_states()
        # state=state_from_lstm
        state = np.reshape(state_from_cnn_lstm, [1, state_size, 2])
        # print(state)
        total_episode_reward = 0  # Initialize total reward for the episode

        for time in range(EPISODE_LENGTH):  # Replace with the desired episode␣
↪length
            action = agent.act(state)
            # print(market_returns_array[time])
            # Get this time state for reward calculation
            # print(state.shape)
            time_state=state[0][time]
            # print(time_state,time,episode)
            next_state, reward, done = env.step(action,time_state)
            next_state = np.reshape(next_state, [1, state_size, 2])
            # print(state.shape)
            agent.remember(state, action, reward, next_state, done)
            state = next_state
            total_episode_reward += reward  # Accumulate the reward obtained at␣
↪each time step
            total_rewards.append(total_episode_reward)
            if done:
                print("Episode: {}/{}, Reward score: {}".format(episode+1,␣
↪EPISODES, total_episode_reward))
                break
            # print(batch_size)
            if len(agent.memory) > batch_size:
                agent.replay(batch_size)
    # Evaluate the performance of the agent
    score = np.mean(total_rewards)
    print("Uncertainty penalty score: ",score, "penalty: ",params)
    if score > best_score:
        best_score = score
        best_params = params

print("Best Uncertainty Penalty:", best_params['uncertainty_penalty'])
```

```
200
100
Episode: 1/10, Reward score: -6063.004422030691
Episode: 2/10, Reward score: -9549.968468211388
Episode: 3/10, Reward score: -6249.005491661543
Episode: 4/10, Reward score: -5644.07216466267
Episode: 6/10, Reward score: -7177.048804268092
Episode: 7/10, Reward score: -16384.20121454646
Episode: 9/10, Reward score: -7317.455371579456
```

```
Episode: 10/10, Reward score: -8345.370684839507
Uncertainty penalty score:  4204.519619832204 penalty:  {'uncertainty_penalty':
0.9}
Episode: 1/10, Reward score: -6036.133147831693
Episode: 3/10, Reward score: -5519.215342364594
Episode: 4/10, Reward score: -6300.47037813598
Episode: 5/10, Reward score: -8776.409181064242
Episode: 6/10, Reward score: -6697.44400869162
Uncertainty penalty score:  7535.5712751618885 penalty:  {'uncertainty_penalty':
0.75}
Episode: 2/10, Reward score: -8316.891145499534
Episode: 3/10, Reward score: -8858.035469048631
Episode: 4/10, Reward score: -18439.884345961273
Episode: 5/10, Reward score: -9026.576022273068
Episode: 6/10, Reward score: -6439.922461102291
Episode: 7/10, Reward score: -8788.208484735613
Episode: 8/10, Reward score: -7095.263076129789
Episode: 9/10, Reward score: -9021.509349508067
Episode: 10/10, Reward score: -5542.1494152086525
Uncertainty penalty score:  -62.84428231357017 penalty:  {'uncertainty_penalty':
0.5}
Episode: 1/10, Reward score: -5941.4282126121125
Episode: 2/10, Reward score: -5627.9067447742855
Episode: 3/10, Reward score: -5902.126321653156
Episode: 6/10, Reward score: -5533.59420222747
Episode: 7/10, Reward score: -7460.3027773291815
Episode: 8/10, Reward score: -6533.349111527528
Episode: 9/10, Reward score: -6646.671358399689
Episode: 10/10, Reward score: -11224.928984382195
Uncertainty penalty score:  2272.9708284957214 penalty:  {'uncertainty_penalty':
0.3}
Episode: 1/10, Reward score: -5712.729722650141
Episode: 2/10, Reward score: -6441.355489091329
Episode: 4/10, Reward score: -15518.175925716632
Episode: 5/10, Reward score: -13002.271649454651
Episode: 6/10, Reward score: -8188.289464894106
Episode: 7/10, Reward score: -13974.018322803791
Episode: 8/10, Reward score: -7330.329554517444
Episode: 9/10, Reward score: -11217.285451886968
Episode: 10/10, Reward score: -10393.149581949123
Uncertainty penalty score:  1510.0281692844144 penalty:  {'uncertainty_penalty':
0.1}
Best Uncertainty Penalty: 0.75
```

[51]:
```
UNCERTAINTY_PENALTY=best_params['uncertainty_penalty']
```

[55]:
```
UNCERTAINTY_PENALTY
```

[55]: 0.75

Episode length hyperparameter tuning

[59]:
```
# Hyperparameters
states=get_states()
state_size = states.size # The actual size of your state
print(state_size)
state_size=int(state_size/2) #The halfed state size for the input size
print(state_size)
action_size = 1  # Percentage defined as a ratio
batch_size = 32

# Define the uncertainty penalty range
episode_length_param_grid = {'episode_length': [10, 15, 20, 30, 40]}

episode_length_best_score = -float('inf')
episode_length_best_params = None

for params in ParameterGrid(episode_length_param_grid):
    # Create the environment and agent
    agent = DQNAgent(state_size, action_size,UNCERTAINTY_PENALTY)
    env = MarketEnvironment(agent)
    total_rewards = []
    # Training the DQN agent
    for episode in range(EPISODES):  # Replace with the desired number of␣
 ↪episodes
        state = env.reset()
        state_from_cnn_lstm = get_states()
        # state=state_from_lstm
        state = np.reshape(state_from_cnn_lstm, [1, state_size, 2])
        # print(state)
        total_episode_reward = 0  # Initialize total reward for the episode

        for time in range(params['episode_length']):  # Replace with the␣
 ↪desired episode length
            action = agent.act(state)
            # print(market_returns_array[time])
            # Get this time state for reward calculation
            # print(state.shape)
            time_state=state[0][time]
            # print(time_state,time,episode)
            next_state, reward, done = env.step(action,time_state)
            next_state = np.reshape(next_state, [1, state_size, 2])
            # print(state.shape)
            agent.remember(state, action, reward, next_state, done)
            state = next_state
```

```
            total_episode_reward += reward  # Accumulate the reward obtained at␣
↪each time step
            total_rewards.append(total_episode_reward)
            if done:
                print("Episode: {}/{}, Reward score: {}".format(episode+1,␣
↪EPISODES, total_episode_reward))
                break
            # print(batch_size)
            if len(agent.memory) > batch_size:
                agent.replay(batch_size)
    # Evaluate the performance of the agent
    score = np.mean(total_rewards)
    print("episode length score: ",score, "episode-length: ",params)
    if score > episode_length_best_score:
        episode_length_best_score = score
        episode_length_best_params = params

print("Best episode length:", episode_length_best_params['episode_length'])
```

```
200
100
Episode: 3/10, Reward score: -7514.893878450878
Episode: 4/10, Reward score: -8108.414768822121
Episode: 5/10, Reward score: -5002.517206079981
Episode: 6/10, Reward score: -6003.914790995475
Episode: 9/10, Reward score: -6065.874533365453
Episode: 10/10, Reward score: -7246.977624097467
episode length score:  4002.8863985294756 episode-length:  {'episode_length':
10}
Episode: 1/10, Reward score: -5948.90192312534
Episode: 3/10, Reward score: -5071.162159959938
Episode: 4/10, Reward score: -6632.867495846647
Episode: 5/10, Reward score: -6543.584676820699
Episode: 6/10, Reward score: -8726.490057497624
Episode: 7/10, Reward score: -6304.366075618569
episode length score:  2618.5309011803297 episode-length:  {'episode_length':
15}
Episode: 1/10, Reward score: -23131.83133804807
Episode: 2/10, Reward score: -7789.075528426594
Episode: 3/10, Reward score: -5239.871150720246
Episode: 4/10, Reward score: -7742.736424340098
Episode: 5/10, Reward score: -9055.207442352337
Episode: 6/10, Reward score: -5384.957058913709
Episode: 7/10, Reward score: -5085.739031555545
Episode: 9/10, Reward score: -8842.803100219884
Episode: 10/10, Reward score: -12905.988580692312
episode length score:  2402.814419473477 episode-length:  {'episode_length': 20}
```

```
Episode: 1/10, Reward score: -7383.13254225711
Episode: 2/10, Reward score: -6231.582825309159
Episode: 3/10, Reward score: -7322.64004639538
Episode: 4/10, Reward score: -5860.466775306031
Episode: 5/10, Reward score: -6787.224188241367
Episode: 6/10, Reward score: -11968.475888811656
Episode: 7/10, Reward score: -6267.069722719247
Episode: 8/10, Reward score: -5188.147798355685
Episode: 9/10, Reward score: -21901.35846510256
episode length score:  13637.196762127396 episode-length:  {'episode_length':
30}
Episode: 1/10, Reward score: -7121.984194614062
Episode: 2/10, Reward score: -5622.122284854211
Episode: 3/10, Reward score: -5217.78763845803
Episode: 4/10, Reward score: -9366.542380490693
Episode: 5/10, Reward score: -5943.168394561837
Episode: 6/10, Reward score: -10230.137009239606
Episode: 7/10, Reward score: -5205.619187357219
Episode: 8/10, Reward score: -7263.03967019254
Episode: 9/10, Reward score: -5614.408801278276
Episode: 10/10, Reward score: -8461.80590322882
episode length score:  -1078.3637372817398 episode-length:  {'episode_length':
40}
Best episode length: 30
```

[60]:
```
EPISODE_LENGTH=episode_length_best_params['episode_length']
```

[63]:
```
EPISODE_LENGTH
```

[63]: 30

Number of episodes hyperparameter tuning

[64]:
```
# Hyperparameters
states=get_states()
state_size = states.size # The actual size of your state
print(state_size)
state_size=int(state_size/2) #The halfed state size for the input size
print(state_size)
action_size = 1  # Percentage defined as a ratio
batch_size = 32

# Define the uncertainty penalty range
episodes_param_grid = {'episodes': [10, 15, 20, 30, 40]}

episodes_best_score = -float('inf')
episodes_best_params = None
```

```python
for params in ParameterGrid(episodes_param_grid):
    # Create the environment and agent
    agent = DQNAgent(state_size, action_size,UNCERTAINTY_PENALTY)
    env = MarketEnvironment(agent)
    total_rewards = []
    # Training the DQN agent
    for episode in range(params['episodes']):  # Replace with the desired number of episodes
        state = env.reset()
        state_from_cnn_lstm = get_states()
        # state=state_from_lstm
        state = np.reshape(state_from_cnn_lstm, [1, state_size, 2])
        # print(state)
        total_episode_reward = 0  # Initialize total reward for the episode

        for time in range(EPISODE_LENGTH):  # Replace with the desired episode length
            action = agent.act(state)
            # print(market_returns_array[time])
            # Get this time state for reward calculation
            # print(state.shape)
            time_state=state[0][time]
            # print(time_state,time,episode)
            next_state, reward, done = env.step(action,time_state)
            next_state = np.reshape(next_state, [1, state_size, 2])
            # print(state.shape)
            agent.remember(state, action, reward, next_state, done)
            state = next_state
            total_episode_reward += reward  # Accumulate the reward obtained at each time step
            total_rewards.append(total_episode_reward)
            if done:
                print("Episode: {}/{}, Reward score: {}".format(episode+1, params['episodes'], total_episode_reward))
                break
            # print(batch_size)
            if len(agent.memory) > batch_size:
                agent.replay(batch_size)
    # Evaluate the performance of the agent
    score = np.mean(total_rewards)
    print("episodes score: ",score, "episodes: ",params)
    if score > episodes_best_score:
        episodes_best_score = score
        episodes_best_params = params

print("Best episodes:", episodes_best_params['episodes'])
```

```
200
100
Episode: 1/10, Reward score: -9547.92099764064
Episode: 2/10, Reward score: -19491.130564957613
Episode: 3/10, Reward score: -10024.751589229536
Episode: 4/10, Reward score: -7385.885488918299
Episode: 5/10, Reward score: -8483.297983061668
Episode: 6/10, Reward score: -30961.85001328421
Episode: 7/10, Reward score: -7857.853122130756
Episode: 8/10, Reward score: -5147.040591645058
Episode: 9/10, Reward score: -10872.52056523765
Episode: 10/10, Reward score: -5922.218908031953
episodes score:  8424.47220231185 episodes:  {'episodes': 10}
Episode: 1/15, Reward score: -13992.268093297731
Episode: 2/15, Reward score: -6396.056280473265
Episode: 3/15, Reward score: -7684.243311604362
Episode: 4/15, Reward score: -7917.077313554495
Episode: 5/15, Reward score: -12059.955229965899
Episode: 6/15, Reward score: -5081.67413356974
Episode: 7/15, Reward score: -6178.671453084802
Episode: 8/15, Reward score: -7858.8943850660435
Episode: 9/15, Reward score: -5746.677012941835
Episode: 10/15, Reward score: -12095.22381454122
Episode: 11/15, Reward score: -7140.617297148371
Episode: 12/15, Reward score: -6105.6703604599
Episode: 13/15, Reward score: -5710.949185478099
Episode: 14/15, Reward score: -6999.299047145956
Episode: 15/15, Reward score: -9918.068137512153
episodes score:  55.622317160953685 episodes:  {'episodes': 15}
Episode: 1/20, Reward score: -22545.217690916113
Episode: 2/20, Reward score: -10377.999277734925
Episode: 3/20, Reward score: -7055.788709183854
Episode: 4/20, Reward score: -8936.719755403268
Episode: 5/20, Reward score: -6089.114280591746
Episode: 6/20, Reward score: -6880.716036814791
Episode: 7/20, Reward score: -14579.602162626543
Episode: 8/20, Reward score: -5602.7679822662
Episode: 9/20, Reward score: -26470.667196595325
Episode: 11/20, Reward score: -11207.969026847253
Episode: 12/20, Reward score: -12111.67197739595
Episode: 13/20, Reward score: -7512.2334441437715
Episode: 14/20, Reward score: -7793.364381248768
Episode: 15/20, Reward score: -24699.43591983267
Episode: 17/20, Reward score: -5316.22199222263
Episode: 18/20, Reward score: -5423.757947868289
Episode: 19/20, Reward score: -7606.4835895061115
episodes score:  17146.265872188793 episodes:  {'episodes': 20}
Episode: 1/30, Reward score: -15705.124984048209
```

```
Episode: 2/30, Reward score: -8698.040682956014
Episode: 3/30, Reward score: -6326.182876898401
Episode: 4/30, Reward score: -5533.113990165937
Episode: 5/30, Reward score: -16428.328174379643
Episode: 6/30, Reward score: -12317.546056548792
Episode: 7/30, Reward score: -19188.293407083667
Episode: 8/30, Reward score: -6010.074393695339
Episode: 9/30, Reward score: -10593.387015308097
Episode: 10/30, Reward score: -35651.552491361304
Episode: 11/30, Reward score: -14040.244813778238
Episode: 12/30, Reward score: -8936.553297559767
Episode: 13/30, Reward score: -8563.332651987752
Episode: 14/30, Reward score: -5988.395046565107
Episode: 15/30, Reward score: -5904.896595731241
Episode: 16/30, Reward score: -10644.352122942375
Episode: 17/30, Reward score: -9751.728192369912
Episode: 19/30, Reward score: -5445.635919005311
Episode: 20/30, Reward score: -5901.735556051855
Episode: 21/30, Reward score: -5585.486963066371
Episode: 23/30, Reward score: -8250.163156311384
Episode: 27/30, Reward score: -8064.666045770459
Episode: 29/30, Reward score: -5426.076605895049
Episode: 30/30, Reward score: -5773.224155249209
episodes score:  5950.471709423819 episodes:  {'episodes': 30}
Episode: 2/40, Reward score: -41744.432647928414
Episode: 3/40, Reward score: -6429.234683516068
Episode: 4/40, Reward score: -7958.908786562927
Episode: 5/40, Reward score: -6321.469981364784
Episode: 6/40, Reward score: -5966.808654236077
Episode: 7/40, Reward score: -6094.220896333914
Episode: 8/40, Reward score: -8785.246779108424
Episode: 10/40, Reward score: -11903.362407683264
Episode: 11/40, Reward score: -5448.345647715407
Episode: 13/40, Reward score: -11747.968152868818
Episode: 15/40, Reward score: -7803.5562654406485
Episode: 16/40, Reward score: -5835.769212658717
Episode: 17/40, Reward score: -5454.169757990303
Episode: 19/40, Reward score: -5098.157949137241
Episode: 20/40, Reward score: -7318.026649656698
Episode: 21/40, Reward score: -13774.39083637106
Episode: 22/40, Reward score: -9352.466299888129
Episode: 23/40, Reward score: -7296.076138474236
Episode: 27/40, Reward score: -5711.375270646135
Episode: 31/40, Reward score: -6807.3502658967045
Episode: 32/40, Reward score: -5127.010799433947
Episode: 34/40, Reward score: -7945.576947995344
Episode: 37/40, Reward score: -5679.187146713366
episodes score:  18054.251981021655 episodes:  {'episodes': 40}
```

```
Best episodes: 40
```

[65]:

```
EPISODES=episodes_best_params['episodes']
```

Best hyperparameters - EPISODES=40 - EPISODE_LENGTH=30 - UNCERTAINTY_PENALTY=0.75

[6]:

```
EPISODES=40
EPISODE_LENGTH=30
UNCERTAINTY_PENALTY=0.75
```

[66]:

```
# Hyperparameters
states=get_states()
state_size = states.size # The actual size of your state
print(state_size)
state_size=int(state_size/2) #The halfed state size for the input size
print(state_size)
action_size = 1  # Percentage defined as a ratio
batch_size = 32
# # market return

# Create the environment and agent
agent = DQNAgent(state_size, action_size, UNCERTAINTY_PENALTY)
env = MarketEnvironment(agent)




# Training the DQN agent
for episode in range(EPISODES):  # Replace with the desired number of episodes
    state = env.reset()
    state_from_cnn_lstm = get_states()
    # state=state_from_lstm
    state = np.reshape(state_from_cnn_lstm, [1, state_size, 2])
    # print(state)
    total_episode_reward = 0  # Initialize total reward for the episode

    for time in range(EPISODE_LENGTH):  # Replace with the desired episode␣
 ↪length
        action = agent.act(state)
        # print(market_returns_array[time])
        # Get this time state for reward calculation
        # print(state.shape)
        time_state=state[0][time]
        # print(time_state,time,episode)
        next_state, reward, done = env.step(action,time_state)
        next_state = np.reshape(next_state, [1, state_size, 2])
        # print(state.shape)
        agent.remember(state, action, reward, next_state, done)
```

```
        state = next_state
        total_episode_reward += reward  # Accumulate the reward obtained at␣
↪each time step
        if done:
            print("Episode: {}/{}, Reward score: {}".format(episode+1,␣
↪EPISODES, total_episode_reward))
            break
        # print(batch_size)
        if len(agent.memory) > batch_size:
            agent.replay(batch_size)
```

```
200
100
Episode: 1/40, Reward score: -5165.778725524984
Episode: 2/40, Reward score: -10948.498673451631
Episode: 3/40, Reward score: -9786.253994051967
Episode: 4/40, Reward score: -68681.48103538027
Episode: 6/40, Reward score: -6552.179274709281
Episode: 7/40, Reward score: -9346.62403099326
Episode: 8/40, Reward score: -23157.585012660704
Episode: 9/40, Reward score: -8271.590287196754
Episode: 10/40, Reward score: -16941.948463074146
Episode: 11/40, Reward score: -6773.583091827699
Episode: 12/40, Reward score: -24950.99464415438
Episode: 15/40, Reward score: -5382.734334431651
Episode: 17/40, Reward score: -6279.206142442916
Episode: 19/40, Reward score: -6527.869466981507
Episode: 20/40, Reward score: -5345.633362981011
Episode: 21/40, Reward score: -8393.963089852923
Episode: 24/40, Reward score: -5504.270658906927
Episode: 28/40, Reward score: -8336.709180996391
Episode: 29/40, Reward score: -8419.436740012698
Episode: 36/40, Reward score: -11669.669611192789
```

5.2 Save model weights

[67]:
```
# Save DQNAgent object weights
agent.model.save_weights('trained_qql_weights.h5')
# Assuming your agent is called 'agent'


# Save the agent's configurations using pickle
agent_config = {
    'state_size': agent.state_size,
    'action_size': agent.action_size,
    # Add any other relevant configurations of your agent here
}
```

```
print(agent_config)
with open("trained_qql_agent_config.pkl", "wb") as config_file:
    pickle.dump(agent_config, config_file)
```

```
{'state_size': 100, 'action_size': 1}
```

6 Backtest the models

Collect market data

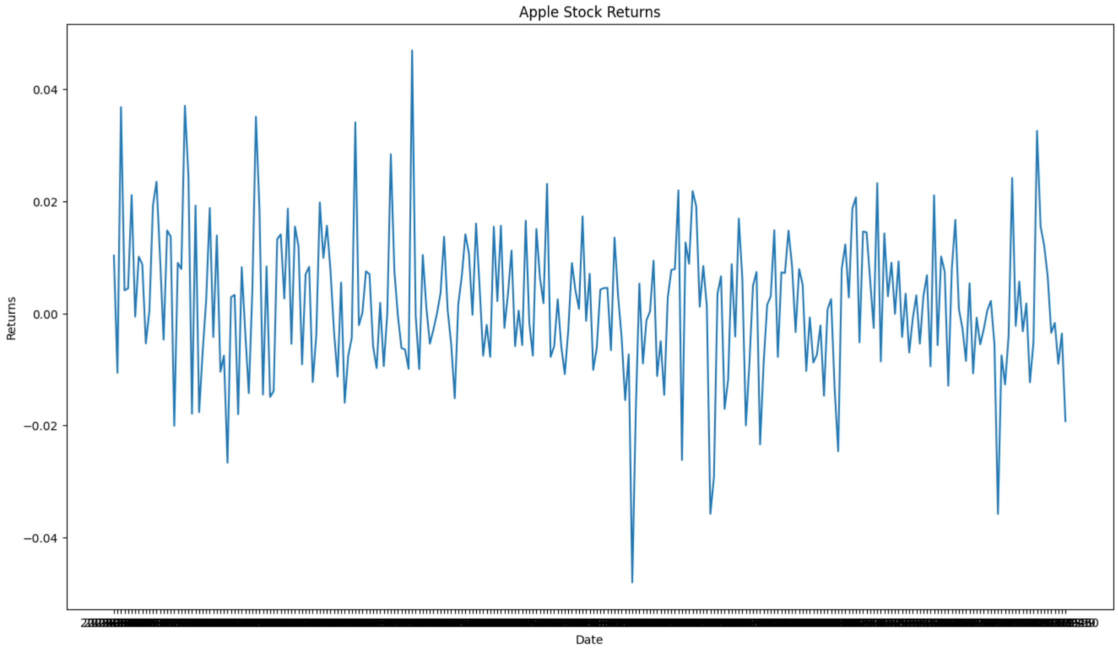
[68]:
```
# Define the start and end dates for the live market data
start_date_live = '2023-01-01'
end_date_live = '2024-01-31'

# Fetch the data using the Yahoo Finance API
apple_data_live = yf.download('AAPL', start=start_date_live, end=end_date_live)
# Display the first few rows of the data
print(apple_data_live.head())
apple_data_live.to_csv("apple_stock_prices_live.csv")
```

```
[*********************100%%**********************]  1 of 1 completed

                  Open        High         Low       Close   Adj Close  \
Date
2023-01-03  130.279999  130.899994  124.169998  125.070000  124.216301
2023-01-04  126.889999  128.660004  125.080002  126.360001  125.497498
2023-01-05  127.129997  127.769997  124.760002  125.019997  124.166641
2023-01-06  126.010002  130.289993  124.889999  129.619995  128.735245
2023-01-09  130.470001  133.410004  129.889999  130.149994  129.261627

               Volume
Date
2023-01-03  112117500
2023-01-04   89113600
2023-01-05   80962700
2023-01-06   87754700
2023-01-09   70790800
```

[7]:
```
# Load the data from the CSV file
data_live = pd.read_csv("apple_stock_prices_live.csv")
```

[8]:
```
# Calculate the returns
data_live['Returns'] = data_live['Adj Close'].pct_change()



# Drop rows with missing values (NaNs) resulting from the shifting
data_live.dropna(inplace=True)
```

```python
# Create the line plot
plt.plot(data_live["Date"], data_live["Returns"])
plt.title("Apple Stock Returns")
plt.xlabel("Date")
plt.ylabel("Returns")
plt.show()
```



Preprocess for Bayesian CNN-LSTM predictions

[9]:
```python
X_live = []
y_live = []
window_size=100
for i in range(1 , len(data_live) - window_size -1 , 1):
    first = data_live.iloc[i,5]
    # print(first)
    temp = []
    temp2 = []
    for j in range(window_size):
        temp.append((data_live.iloc[i + j, 5] - first) / first)
    temp2.append((data_live.iloc[i + window_size, 5] - first) / first)
    X_live.append(np.array(temp).reshape(100, 1))
    y_live.append(np.array(temp2).reshape(1, 1))


X_live = np.array(X_live)
y_live = np.array(y_live)
```

```
# # Reshape the input data for CNN (channels last)
X_live = X_live.reshape(X_live.shape[0],1,100,1)

print(len(X_live))
print(len(y_live))
```

```
167
167
```

[ ]:
```
# X_live
```

Load the trained and saved Bayesian CNN-LSTM model

[10]:
```
# Load the saved model
loaded_bay_cnn_lstm_model = load_model('complete_bayesian_cnn_lstm.h5')
```

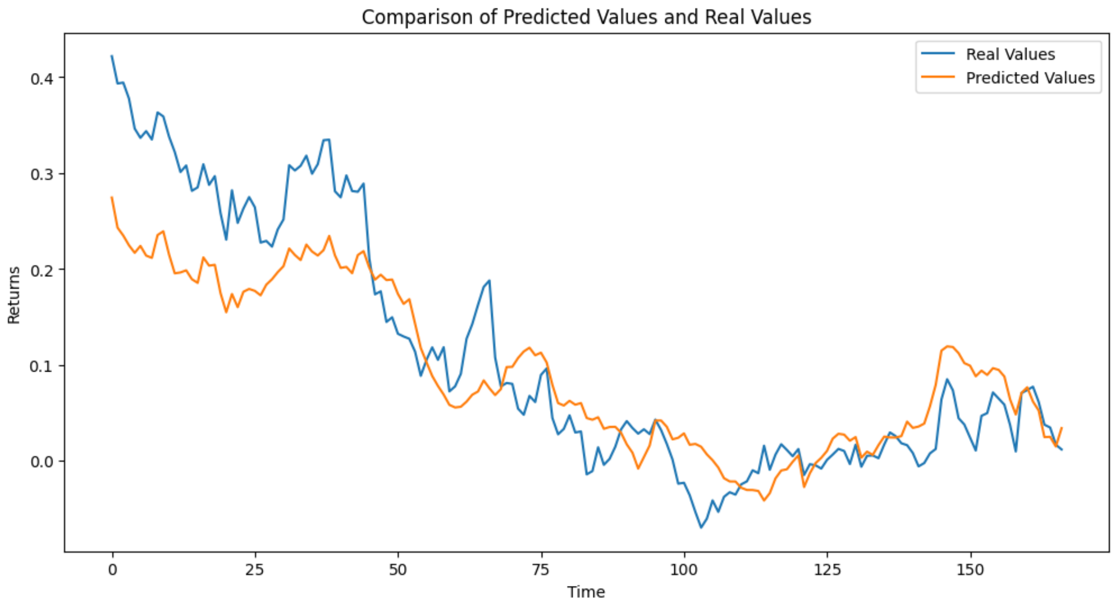
```
WARNING:tensorflow:From D:\sagan\financial engineering\courses\Capstone
project\submissions\codes\.envs\lib\site-packages\keras\src\backend.py:1398: The
name tf.executing_eagerly_outside_functions is deprecated. Please use
tf.compat.v1.executing_eagerly_outside_functions instead.

WARNING:tensorflow:From D:\sagan\financial engineering\courses\Capstone
project\submissions\codes\.envs\lib\site-packages\keras\src\backend.py:6642: The
name tf.nn.max_pool is deprecated. Please use tf.nn.max_pool2d instead.
```

Make Bayesian CNN-LSTM predictions

[11]:
```
# Plot the graph comparing predicted values and real values
y_pred_live = loaded_bay_cnn_lstm_model.predict(X_live)
pred_loss = loaded_bay_cnn_lstm_model.evaluate(X_live, y_live)
print("Prediction loss:", pred_loss)
y_live_list=[]
for i in y_live:
    y_live_list.append(i[0][0])
data_live_2=pd.DataFrame(y_pred_live,columns=["pred"])
data_live_2["real"]=y_live_list
plt.figure(figsize=(12, 6))
plt.plot(data_live_2['real'], label='Real Values')
plt.plot(data_live_2['pred'], label='Predicted Values')
plt.xlabel('Time')
plt.ylabel('Returns')
plt.title('Comparison of Predicted Values and Real Values')
plt.legend()
plt.show()
```

```
6/6 [==============================] - 3s 14ms/step
WARNING:tensorflow:From D:\sagan\financial engineering\courses\Capstone
project\submissions\codes\.envs\lib\site-
packages\keras\src\utils\tf_utils.py:492: The name tf.ragged.RaggedTensorValue
```

```
is deprecated. Please use tf.compat.v1.ragged.RaggedTensorValue instead.

6/6 [==============================] - 3s 24ms/step - loss: 0.0038 - mse: 0.0038
- mae: 0.0482
Prediction loss: [0.0037900698371231556, 0.0037900698371231556,
0.048176851123571396]
```



Estimate uncertainty

[14]:
```
num_predictions_live = 100
predictions_live = []

for _ in range(num_predictions_live):
    enable_dropout(loaded_bay_cnn_lstm_model)
    pred = loaded_bay_cnn_lstm_model.predict(X_live,verbose=0)
    predictions_live.append(pred)

predictions_live = np.array(predictions_live)
```

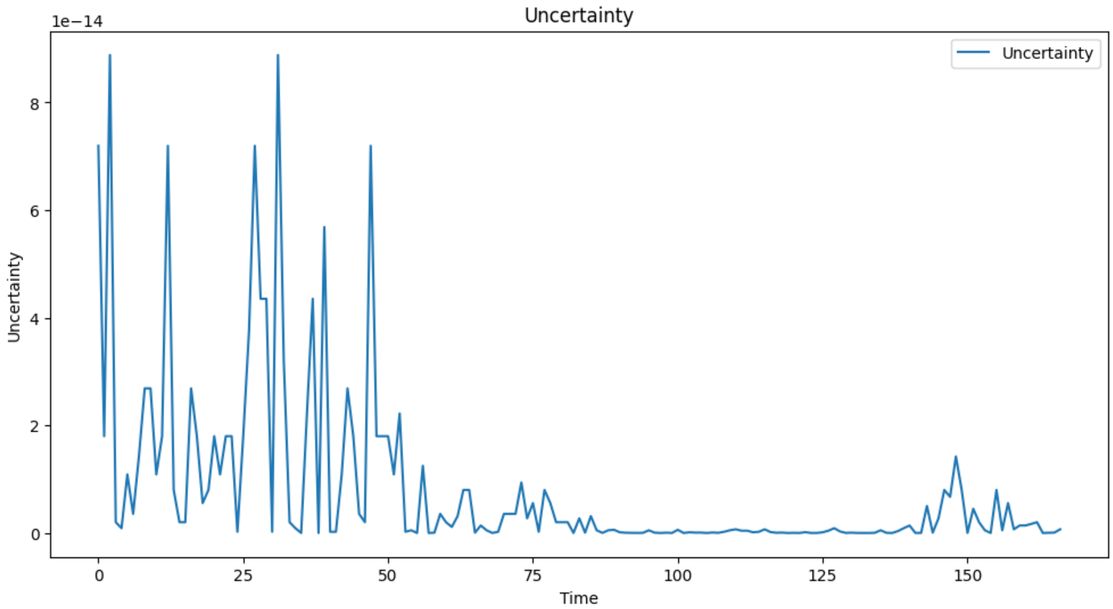
Aggregate uncertianty

[15]:
```
mean_prediction_live = np.mean(predictions_live, axis=0)
uncertainty_live = np.var(predictions_live, axis=0)
```

[ ]:
```
uncertainty_live
```

[16]:
```
# uncertainty
```

```
plt.figure(figsize=(12, 6))
plt.plot(uncertainty_live, label='Uncertainty')
plt.xlabel('Time')
plt.ylabel('Uncertainty')
plt.title('Uncertainty')
plt.legend()
plt.show()
```



[ ]:
```
y_pred_live.shape
```

Load the Deep Q-learning weights

[32]:
```
# Function to get states from your Bayesian CNN-LSTM model and incorporate␣
↪uncertainty
def get_states_live():
    # create an extended state that incorporated uncertainty estimation
    # and the predictionsd
    extended_state = np.concatenate(
        (y_pred_live[:100,:],
         uncertainty_live[:100,:]),
        axis=1
    )
    return extended_state


# # Hyperparameters
states=get_states_live()
```

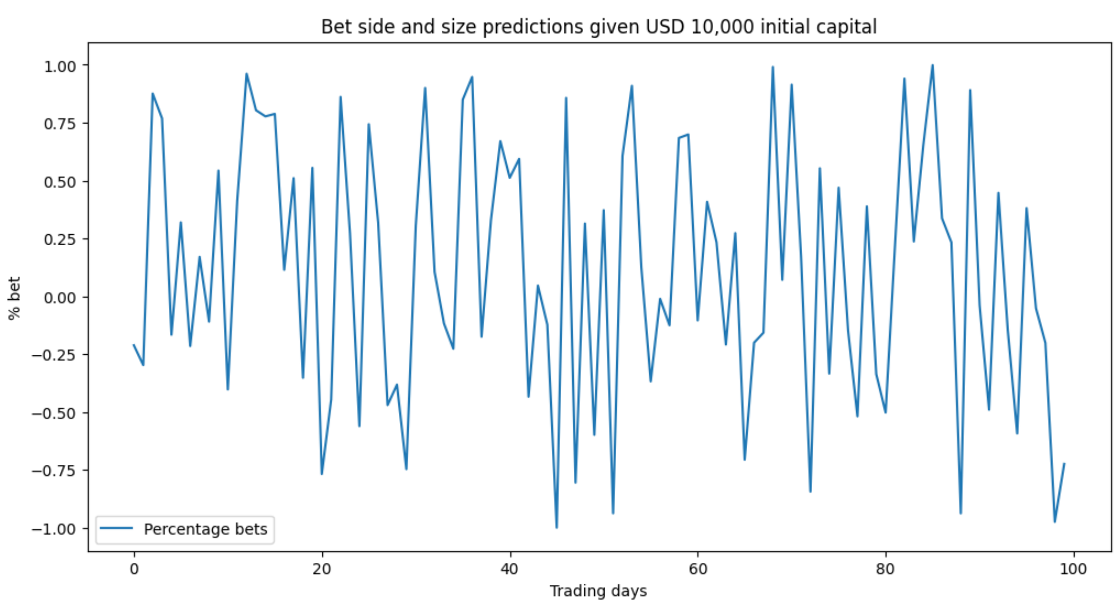
```
state_size = states.size # The actual size of your state
state_size=int(state_size/2) #The halfed state size for the input size
print(state_size)
action_size = 1  # Percentage defined as a ratio
batch_size = 32
# market return
# Load trained model weights
loaded_dqq_agent = DQNAgent(state_size, action_size,UNCERTAINTY_PENALTY)
loaded_dqq_agent.model.load_weights('trained_qql_weights.h5')
```

100

Make bet size predictions

[39]:
```
# Predict actions (sizes of bets)
actions_live = []
for state in states:
    action = loaded_dqq_agent.act(state)
    actions_live.append(action)

# print("Predicted actions:", actions_live)
```

[41]:
```
plt.figure(figsize=(12, 6))
plt.plot(actions_live, label='Percentage bets')
plt.xlabel('Trading days')
plt.ylabel('% bet')
plt.title('Bet side and size predictions given USD 10,000 initial capital')
plt.legend()
plt.show()
```



[58]:
```python
def evaluate_actions(actions, market_returns,␣
↪initial_capital=10000,num_trades=10):
    """
    Evaluate the performance of actions in the market.

    Args:
    - actions (list): List of actions taken by the agent (sizes of bets).
    - market_returns (numpy.ndarray): Array of actual market returns.
    - initial_capital (float): Initial capital for trading. Default is 10000.

    Returns:
    - cumulative_return (float): Cumulative return after trading.
    """
    capital = initial_capital
    num_trades = num_trades
    total_return = 0
    profit_loss=[]
    cum_capital=[]
    cum_capital.append(initial_capital)
    profit_loss.append(0)
    for i, action in enumerate(actions):
        if i>num_trades:
            break
        # Calculate bet size based on the selected action
        bet_size = abs(action) * capital

        # Calculate transaction cost based on the bet size (assuming 1%␣
↪transaction cost)
        transaction_cost = 0.01 * bet_size

        # Subtract transaction cost from capital
        capital -= transaction_cost
        # Calculate the return based on the market return and the direction of␣
↪the trade
        # For a long position, return is market return * bet size
        # For not taking any position, return is 0
        if action > 0:
            return_direction = 1
        elif action<0:
            return_direction = -1
        else:
            return_direction = 0
        return_amount = return_direction * market_returns[i][0][0] * bet_size
        profit_loss.append(return_amount)
        # Calculate yield size (bet size + market return amount)
```

```
        # print("Action=",action)
        # print("bet_size=",bet_size)
        # print("Market return",market_returns[i][0][0])
        yield_size = return_amount + bet_size
        # print("Return amount=",return_amount)
        # print("yield_size=",yield_size)

        # Update capital and holding based on action
        if action > 0:
            # Going long
            capital += return_amount
        elif action < 0:
            # Going short
            capital += return_amount

        # Increment total reward
        total_return += return_amount
        cum_capital.append(capital)
    # Calculate cumulative return
    cumulative_return = ((total_return)/initial_capital)*100

    return total_return,cumulative_return,num_trades,profit_loss,cum_capital
```

[59]:
```
cum_reward=evaluate_actions(
    actions=actions_live,
    market_returns=y_live,
    num_trades=10
)
```

[60]:
```
len(cum_reward[3])
```

[60]: 12

[61]:
```
len(cum_reward[4])
```

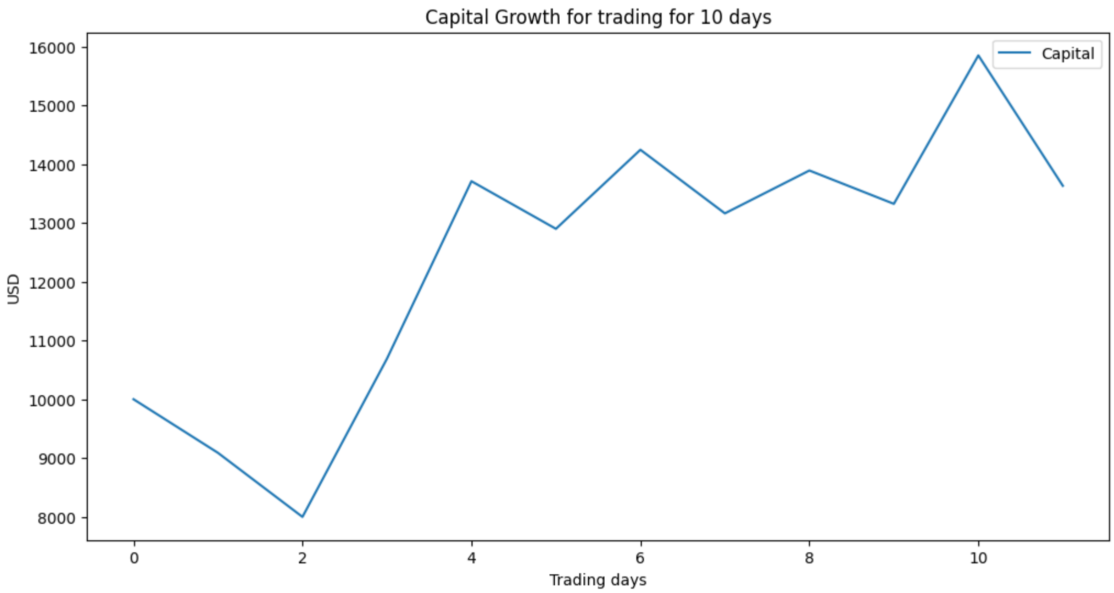
[61]: 12

[62]:
```
data_live_4=pd.DataFrame(cum_reward[4],columns=["Capital"])
data_live_4['profit']=cum_reward[3]
data_live_4.head()
```

[62]:

	Capital	profit
0	10000.000000	0.000000
1	9087.277664	-891.589704
2	7997.720271	-1062.549034
3	10690.089239	2762.415694
4	13710.352394	3102.408912

[63]:
```
plt.figure(figsize=(12, 6))
plt.plot(data_live_4['Capital'], label='Capital')
plt.xlabel('Trading days')
plt.ylabel('USD')
plt.title('Capital Growth for trading for 10 days')
plt.legend()
plt.show()
```



[64]:
```
plt.figure(figsize=(12, 6))
plt.plot(data_live_3['profit'], label='Percentage profit (10 bets)')
plt.xlabel('Trading days')
plt.ylabel('%')
plt.title('Profit or loss')
plt.legend()
plt.show()
```

[65]:
```
print(
    f"Total profit = {cum_reward[0]}",
    f"%-profit = {cum_reward[1]}",
    f"Total trades = {cum_reward[2]}"
    )
```

```
Total profit = 4100.65129072707 %-profit = 41.0065129072707 Total trades = 10
```

Agents performance based on number of trades allowed to place

[66]:
```
num_trades_profits=[]
num_trades_percentage_profits=[]
num_trades_cum_reward=[]
for i in range(1,101):
    cum_reward_=evaluate_actions(
        actions=actions_live,
        market_returns=y_live,
        num_trades=i
    )
    num_trades_profits.append(cum_reward_[0])
    num_trades_percentage_profits.append(cum_reward_[1])
    #Get the cummulative capital on the last trading day
    num_trades_cum_reward.append(cum_reward_[4][-1])
```

[67]:
```
trade_data={
    "profit":num_trades_profits,
    "percentage_profit":num_trades_percentage_profits,
    "capital":num_trades_cum_reward
```

```
}
data_live_5=pd.DataFrame(trade_data)
```

[68]:
```
data_live_5.head(10)
```

[68]:

	profit	percentage_profit	capital
0	-1954.138739	-19.541387	7997.720271
1	808.276956	8.082770	10690.089239
2	3910.685867	39.106859	13710.352394
3	3123.213387	31.232134	12900.147327
4	4509.934719	45.099347	14245.690922
5	3458.147166	34.581472	13163.313908
6	4210.003584	42.100036	13892.730357
7	3657.817458	36.578175	13325.343013
8	6256.113527	62.561135	15851.280882
9	4100.651291	41.006513	13632.068928

[69]:
```
data_live_5.tail(10)
```

[69]:

	profit	percentage_profit	capital
90	65974.558013	659.745580	55313.672747
91	66679.617172	666.796172	55771.533908
92	66405.577536	664.055775	55414.648817
93	65484.135482	654.841355	54165.056098
94	66374.011268	663.740113	54848.662237
95	66282.135669	662.821357	54728.335955
96	66085.458594	660.854586	54421.460483
97	66004.787013	660.047870	53810.673991
98	66924.527279	669.245273	54340.904405
99	66924.527279	669.245273	54340.904405

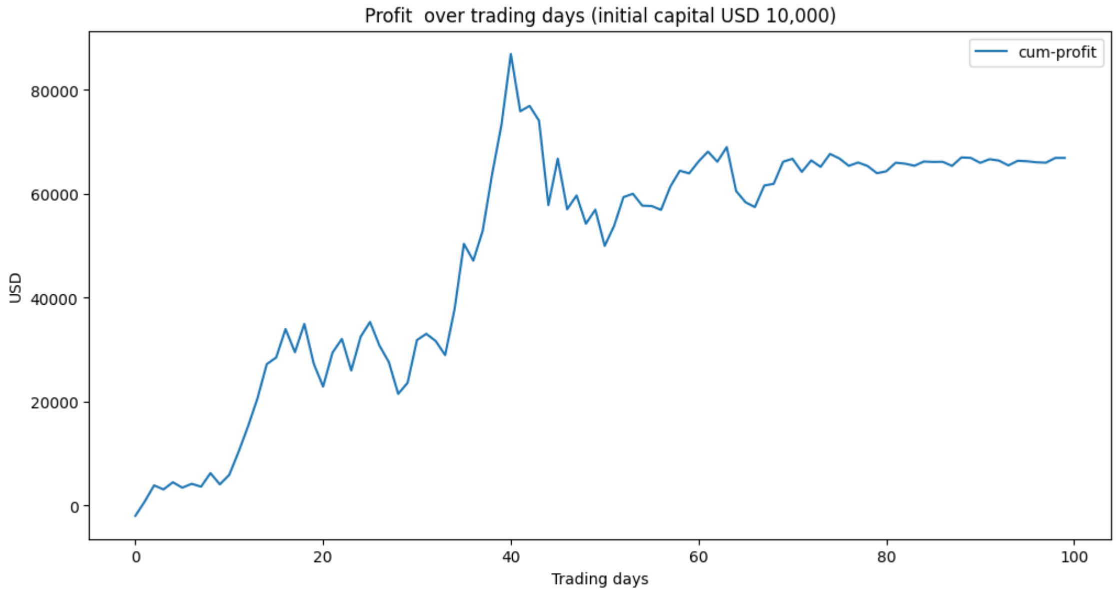
[70]:
```
data_live_5.describe()
```

[70]:

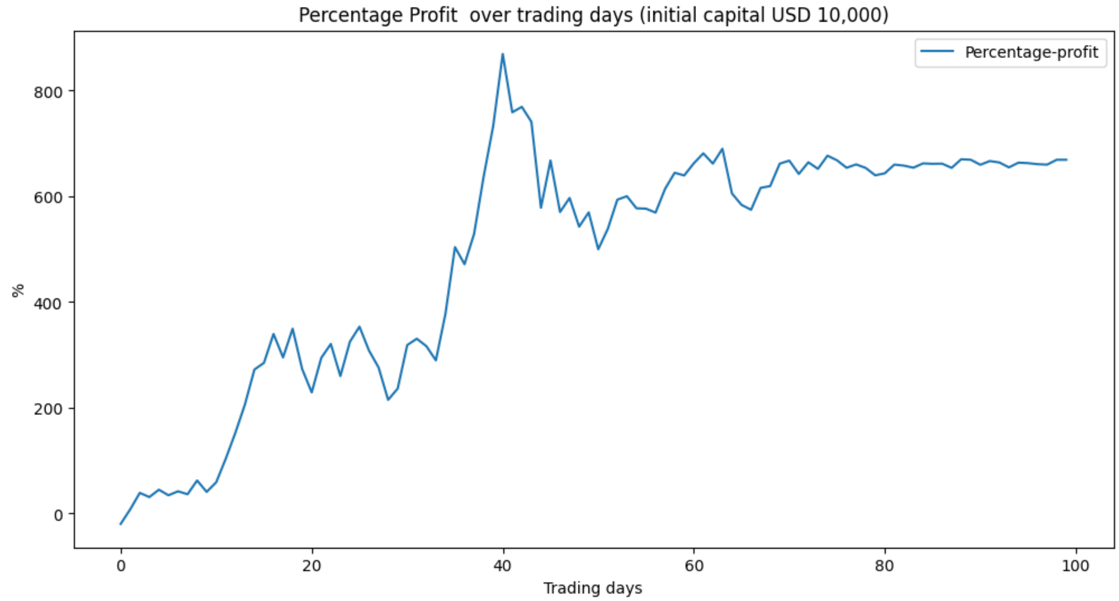
	profit	percentage_profit	capital
count	100.000000	100.000000	100.000000
mean	48667.380755	486.673808	48741.286118
std	22806.859535	228.068595	17488.590802
min	-1954.138739	-19.541387	7997.720271
25%	30497.879862	304.978799	37347.147885
50%	59533.747939	595.337479	55364.160782
75%	66163.825686	661.638257	58871.838426
max	86931.182176	869.311822	90367.524775

[71]:
```
plt.figure(figsize=(12, 6))
plt.plot(data_live_5['profit'], label="cum-profit")
plt.xlabel('Trading days')
plt.ylabel('USD')
```

```
plt.title('Profit  over trading days (initial capital USD 10,000)')
plt.legend()
plt.show()
```



[72]:
```
plt.figure(figsize=(12, 6))
plt.plot(data_live_5['percentage_profit'], label="Percentage-profit")
plt.xlabel('Trading days')
plt.ylabel('%')
plt.title('Percentage Profit  over trading days (initial capital USD 10,000)')
plt.legend()
plt.show()
```




```
[73]: plt.figure(figsize=(12, 6))
      plt.plot(data_live_5['capital'], label='Capital')
      plt.xlabel('Trading days')
      plt.ylabel('USD')
      plt.title('Capital Growth for trading for over trading days')
      plt.legend()
      plt.show()
```

7 6. Market timing using Q-learning agent without uncertainty (CNN-LSTM Q-learning)

[74]:
```
# Function to get states from your Bayesian CNN-LSTM model and incorporate␣
↪uncertainty
def get_states_cnn_lstm():
    # We limit the state size to 100*2
    # This is necessary to maintain consistency
    return y_pred[:100,:]
```

[106]:
```
# The DQN agent
class DQNAgentCNNLSTM:
    def __init__(self, state_size, action_size):
        self.state_size = state_size
        self.action_size = action_size
        self.memory = deque(maxlen=200)  # Experience replay buffer
        self.gamma = 0.95  # Discount factor
        self.epsilon = 1.0  # Exploration-exploitation trade-off
        self.epsilon_decay = 0.995
        self.epsilon_min = 0.01
        self.learning_rate = 0.001
        self.model = self._build_model()

    def _huber_loss(self,y_true, y_pred, clip_delta=1.0):
        error = y_true - y_pred
        cond  = keras_b.abs(error) <= clip_delta

        squared_loss = 0.5 * keras_b.square(error)
        quadratic_loss = (
                    0.5 * keras_b.square(clip_delta) +
                    clip_delta * (keras_b.abs(error) - clip_delta)
                )

        return keras_b.mean(tf.where(cond, squared_loss, quadratic_loss))

    def _build_model(self):
        model = Sequential()
        model.add(Flatten(input_shape=(state_size,1)))  # Flatten layer to␣
↪reshape input
        model.add(Dense(24, activation='relu'))
        model.add(Dense(24, activation='relu'))
        model.add(Dense(self.action_size, activation='linear'))
        model.compile(
            loss=self._huber_loss,
            optimizer=Adam(learning_rate=self.learning_rate)
        )
        # model = Sequential()
```

```
        # model.add(Dense(24, activation='relu'))
        # model.add(Dense(24, activation='relu'))
        # model.add(Dense(self.action_size, activation='linear'))
        # model.compile(loss='mse', optimizer=Adam(learning_rate=self.
↪learning_rate))
        return model

    def remember(self, state, action, reward, next_state, done):
        # print(state.shape)
        self.memory.append((state, action, reward, next_state, done))

    def act(self, state,current_holding=0):
        if np.random.rand() <= self.epsilon:
            # Randomly select action from the action space: short, do nothing,␣
↪long
            return np.random.uniform(-1, 1)
        else:
            # Use the Q-network to select action based on state
            return np.argmax(self.model.predict(state,verbose=0)[0])

    def replay(self, batch_size):
        minibatch = random.sample(self.memory, batch_size)
        for state, action, reward, next_state, done in minibatch:
            target = reward
            # print(next_state.shape)
            if not done:
                # print(self.model.predict(next_state))
                target = reward + self.gamma * np.amax(self.model.
↪predict(next_state,verbose=0)[0])
            # print(state.shape)
            target_f = self.model.predict(state,verbose=0)
            # print(target_f)
            target_f[0][0] = target
            self.model.fit(state, target_f, epochs=1, verbose=0)
        if self.epsilon > self.epsilon_min:
            self.epsilon *= self.epsilon_decay

# The Market environment
class MarketEnvironmentCNNLSTM:
    def __init__(self, max_episode_length=100, min_available_capital=10,␣
↪max_trades=None, profit_target=None, stop_loss=-5000):
        self.state_size = state_size  # The actual size of your state
        self.action_size = 1  # Example: Buy, Sell, Hold
        self.initial_capital = 10000  # Initial available capital
        self.transaction_cost = 0.01  # Transaction charge (1%)
        self.current_capital = self.initial_capital
        self.max_episode_length = max_episode_length
```

```
        self.min_available_capital = min_available_capital
        self.max_trades = max_trades
        self.profit_target = profit_target
        self.stop_loss = stop_loss
        self.num_trades = 0
        self.total_reward = 0

    def reset(self):
        # Reset logic
        self.current_capital = self.initial_capital
        self.num_trades = 0
        self.total_reward = 0
        # print(self.state_size)
        return np.random.rand(self.state_size)

    def step(self, action,time_state):
        # Extract market returns and uncertainty from the state
        # print(time_state)
        market_returns = time_state  # First column contains predicted market␣
↪returns
        # Simulated step function, returns next_state, reward, done
        next_state = np.random.rand(self.state_size)

        # Calculate bet size based on the selected action
        bet_size = abs(action) * self.current_capital

        # Calculate transaction cost based on the bet size
        total_transaction_cost=self.transaction_cost * bet_size
        # Subtract the transaction cost
        self.current_capital -= total_transaction_cost
        # Calculate the return based on the market return and the direction of␣
↪the trade
        # For a long position, return is market return * bet size
        # For not taking any position, return is 0
        if action > 0:
            return_direction = 1
        elif action<0:
            return_direction = -1
        else:
            return_direction = 0
        return_amount = return_direction * market_returns * bet_size
        yield_size=return_amount+bet_size
        if action > 0:
            # Adjust available capital based on bet size
            self.current_capital += return_amount

        # If action == 0, it means the agent wants to close the position
```

```
        elif action == 0:
            # Adjust available capital based on the current holding
            self.current_capital += return_amount
        # Calculate reward based on market return, transaction charges, and␣
↪uncertainty
        reward = return_amount
        # Increment total reward
        self.total_reward += reward

        # Increment number of trades
        self.num_trades += 1
         # Check termination conditions
        done = False
        if self.num_trades >= self.max_episode_length:
            done = True
        elif self.current_capital <= self.min_available_capital:
            done = True
        elif self.max_trades is not None and self.num_trades >= self.max_trades:
            done = True
        elif self.profit_target is not None and self.total_reward >= self.
↪profit_target:
            done = True
        elif self.stop_loss is not None and self.total_reward <= self.stop_loss:
            done = True
        return next_state, reward, done
```

[107]:

```
# Hyperparameters
states=get_states_cnn_lstm()
state_size = states.size # The actual size of your state
print(state_size)
state_size=int(state_size) #The halfed state size for the input size
print(state_size)
action_size = 1  # Percentage defined as a ratio
batch_size = 32
# # market return

# Create the environment and agent
env_cnn_lstm = MarketEnvironmentCNNLSTM()
agent_cnn_lstm = DQNAgentCNNLSTM(state_size, action_size)


# Training the DQN agent
for episode in range(EPISODES):  # Replace with the desired number of episodes
    state = env_cnn_lstm.reset()
    state_from_cnn_lstm = get_states_cnn_lstm()
    # print(state_from_cnn_lstm)
    # state=state_from_lstm
```

```
    state = np.reshape(state_from_cnn_lstm, [1, state_size])
    # print(state)
    total_episode_reward = 0  # Initialize total reward for the episode

    for time in range(EPISODE_LENGTH):  # Replace with the desired episode␣
↪length
        action = agent_cnn_lstm.act(state)
        # print(market_returns_array[time])
        # Get this time state for reward calculation
        # print(state.shape)
        time_state=state[0][time]
        # print(time_state,time,episode)
        next_state, reward, done = env_cnn_lstm.step(action,time_state)
        # print(next_state)
        next_state = np.reshape(next_state, [1, state_size])
        # print(state.shape)
        agent_cnn_lstm.remember(state, action, reward, next_state, done)
        state = next_state
        total_episode_reward += reward  # Accumulate the reward obtained at␣
↪each time step
        if done:
            print("Episode: {}/{}, Reward score: {}".format(episode+1,␣
↪EPISODES, total_episode_reward))
            break
        # print(batch_size)
        if len(agent_cnn_lstm.memory) > batch_size:
            agent_cnn_lstm.replay(batch_size)
```

```
100
100
Episode: 1/40, Reward score: -36871.98952942268
Episode: 2/40, Reward score: -12170.662096548587
Episode: 3/40, Reward score: -12813.00177065847
Episode: 4/40, Reward score: -5149.315819545296
Episode: 6/40, Reward score: -5128.402012851954
Episode: 8/40, Reward score: -17054.583679573716
Episode: 9/40, Reward score: -8281.370434107723
Episode: 10/40, Reward score: -9740.887670889972
Episode: 11/40, Reward score: -10346.754375778024
Episode: 12/40, Reward score: -5713.344204921372
Episode: 13/40, Reward score: -10176.861175254373
Episode: 14/40, Reward score: -8385.642194472843
Episode: 16/40, Reward score: -6551.540690034107
Episode: 17/40, Reward score: -10330.044298475048
Episode: 18/40, Reward score: -11834.796042148664
Episode: 19/40, Reward score: -10068.3586808166
Episode: 21/40, Reward score: -7848.39345192342
```

```
Episode: 22/40, Reward score: -5783.931098163715
Episode: 24/40, Reward score: -6090.32888460011
Episode: 25/40, Reward score: -6016.371569186742
Episode: 26/40, Reward score: -8542.185659891305
Episode: 30/40, Reward score: -6297.565870995161
Episode: 32/40, Reward score: -5731.231741676888
Episode: 34/40, Reward score: -5134.547641882637
```

Save the cnn-lstm Q-learning agent model

[108]:
```
# Save DQNAgent object weights
agent_cnn_lstm.model.save_weights('trained_qql_weights_cnn_lstm.h5')
# Assuming your agent is called 'agent'


# Save the agent's configurations using pickle
agent_cnn_lstm_config = {
    'state_size': agent_cnn_lstm.state_size,
    'action_size': agent_cnn_lstm.action_size,
    # Add any other relevant configurations of your agent here
}
print(agent_cnn_lstm_config)
with open("trained_qql_agent_config_cnn_lstm.pkl", "wb") as config_file:
    pickle.dump(agent_cnn_lstm_config, config_file)
```

```
{'state_size': 100, 'action_size': 1}
```

7.1 Backtest CNN-LSTM Q-learning agent

load CNN-LSTM Q-learning agent

[111]:
```
# Function to get states from your CNN-LSTM model
def get_states_live_cnn_lstm():
    # We use the predictions from Bayesian  CNN-LSTM without the Uncertainty␣
 ↪estimates
    return y_pred_live[:100,:]


# # Hyperparameters
states=get_states_live_cnn_lstm()
state_size = states.size # The actual size of your state
state_size=int(state_size) #The halfed state size for the input size
print(state_size)
action_size = 1  # Percentage defined as a ratio
batch_size = 32
# market return
# Load trained model weights
loaded_dqq_agent_cnn_lstm = DQNAgentCNNLSTM(
    state_size, action_size
```

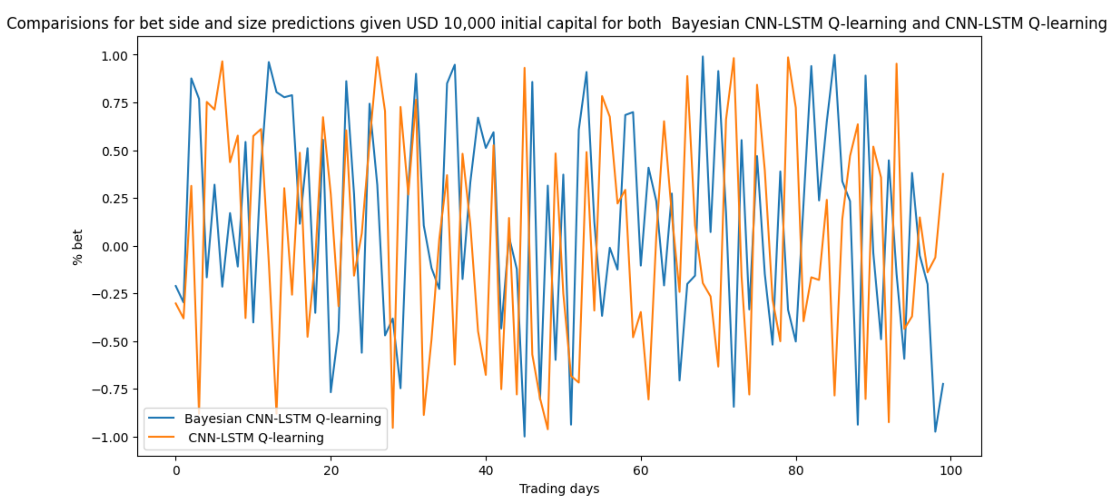
```
)
loaded_dqq_agent_cnn_lstm.model.load_weights('trained_qql_weights_cnn_lstm.h5')
```

100

Make Betsize predictions using CNN-LSTM Q-learning

[265]:
```
# Predict actions (sizes of bets)
actions_live_cnn_lstm = []
for state in states:
    action = loaded_dqq_agent_cnn_lstm.act(state)
    actions_live_cnn_lstm.append(action)

# print("Predicted actions:", actions_live)
```

[266]:
```
plt.figure(figsize=(12, 6))
plt.plot(actions_live, label='Bayesian CNN-LSTM Q-learning')
plt.plot(actions_live_cnn_lstm, label=' CNN-LSTM Q-learning')
plt.xlabel('Trading days')
plt.ylabel('% bet')
plt.title(
    'Comparisions for bet side and size predictions given USD 10,000 initial␣
 ↪capital for both  Bayesian CNN-LSTM Q-learning and CNN-LSTM Q-learning '
         )
plt.legend()
plt.show()
```

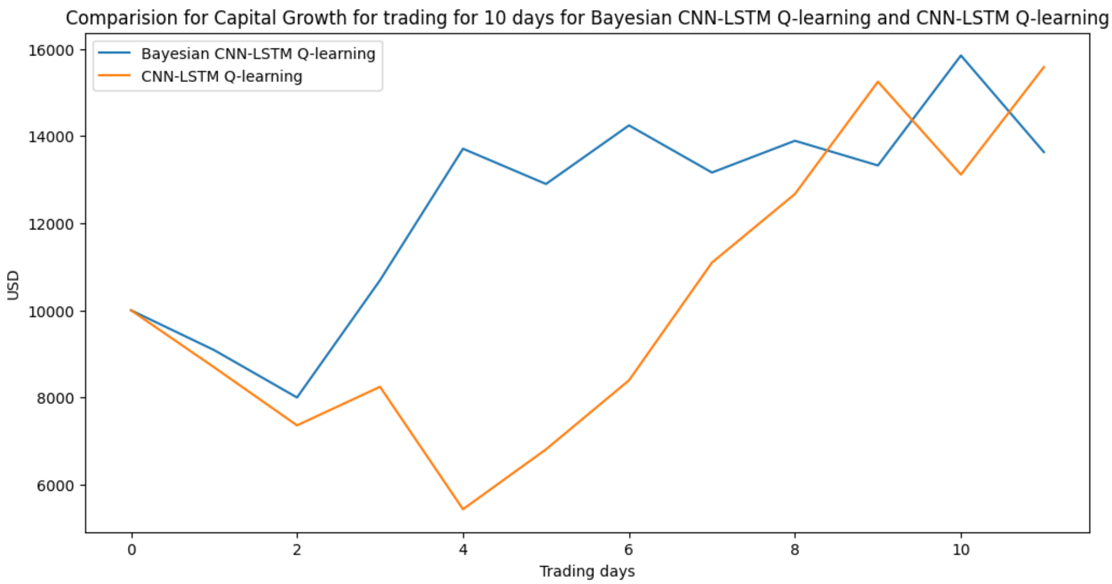


[267]:
```
cum_reward_cnn_lstm=evaluate_actions(
    actions=actions_live_cnn_lstm,
    market_returns=y_live,
    num_trades=10
```

```
)
```

[268]:
```
data_live_4['Capital_cnn_lstm']=cum_reward_cnn_lstm[4]
```

[269]:
```
plt.figure(figsize=(12, 6))
plt.plot(data_live_4['Capital'], label='Bayesian CNN-LSTM Q-learning')
plt.plot(
    data_live_4['Capital_cnn_lstm'],
    label='CNN-LSTM Q-learning'
)
plt.xlabel('Trading days')
plt.ylabel('USD')
plt.title(
    'Comparision for Capital Growth for trading for 10 days for Bayesian␣
 ↪CNN-LSTM Q-learning and CNN-LSTM Q-learning'
)
plt.legend()
plt.show()
```



Profit comparisions

[270]:
```
# Bayesian CNN-LSTM Q-learning
print(
    f"Total profit = {cum_reward[0]}",
    f"%-profit = {cum_reward[1]}",
    f"Total trades = {cum_reward[2]}"
    )
```

Total profit = 4100.65129072707 %-profit = 41.0065129072707 Total trades = 10

[271]:
```
# CNN-LSTM Q-learning
print(
    f"Total profit = {cum_reward_cnn_lstm[0]}",
    f"%-profit = {cum_reward_cnn_lstm[1]}",
    f"Total trades = {cum_reward_cnn_lstm[2]}"
    )
```

Total profit = 6169.304903650239 %-profit = 61.69304903650239 Total trades = 10

General sgents performance based on the number of trades

[272]:
```
num_trades_profits_cnn_lstm=[]
num_trades_percentage_profits_cnn_lstm=[]
num_trades_cum_reward_cnn_lstm=[]
for i in range(1,101):
    cum_reward_=evaluate_actions(
        actions=actions_live_cnn_lstm,
        market_returns=y_live,
        num_trades=i
    )
    num_trades_profits_cnn_lstm.append(cum_reward_[0])
    num_trades_percentage_profits_cnn_lstm.append(cum_reward_[1])
    #Get the cummulative capital on the last trading day
    num_trades_cum_reward_cnn_lstm.append(cum_reward_[4][-1])
```

[273]:
```
trade_databay_cnn_lstm={
    "profit_cnn_lstm":num_trades_profits_cnn_lstm,
    "percentage_profit_cnn_lstm":num_trades_percentage_profits_cnn_lstm,
    "capital_cnn_lstm":num_trades_cum_reward_cnn_lstm
}
data_live_5['profit_cnn_lstm']=num_trades_profits_cnn_lstm
data_live_5['percentage_profit_cnn_lstm']=num_trades_percentage_profits_cnn_lstm
data_live_5['capital_cnn_lstm']=num_trades_cum_reward_cnn_lstm
```

Statistical Summaries of the trade

[274]:
```
data_live_5.describe()
```

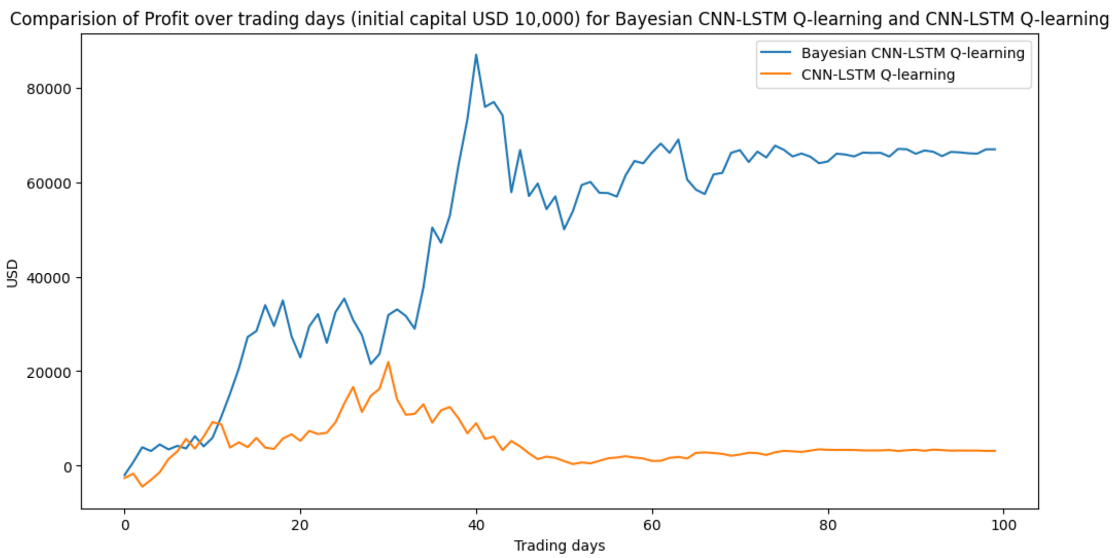
[274]:

	profit	percentage_profit	capital	profit_cnn_lstm	\
count	100.000000	100.000000	100.000000	100.000000	
mean	48667.380755	486.673808	48741.286118	4597.352553	
std	22806.859535	228.068595	17488.590802	4371.249350	
min	-1954.138739	-19.541387	7997.720271	-4409.414467	
25%	30497.879862	304.978799	37347.147885	2245.490590	
50%	59533.747939	595.337479	55364.160782	3253.270459	
75%	66163.825686	661.638257	58871.838426	5963.971613	
max	86931.182176	869.311822	90367.524775	21950.973871	

```
       percentage_profit_cnn_lstm  capital_cnn_lstm  profit_bay_cnn  \
count                  100.000000        100.000000      100.000000
mean                    45.973526      11207.960032     3512.239236
std                     43.712494       5096.115758     2938.303385
min                    -44.094145       5431.670748    -1272.913302
25%                     22.454906       7538.698475     1188.114378
50%                     32.532705       8202.446402     2264.668805
75%                     59.639716      14670.491519     5818.024649
max                    219.509739      29552.931223    11330.556982

       percentage_profit_bay_cnn  capital_bay_cnn
count                 100.000000       100.000000
mean                   35.122392     10818.180620
std                    29.383034      3624.674066
min                   -12.729133      6315.130436
25%                    11.881144      7220.711064
50%                    22.646688     10570.013809
75%                    58.180246     13677.834608
max                   113.305570     20731.833541
```

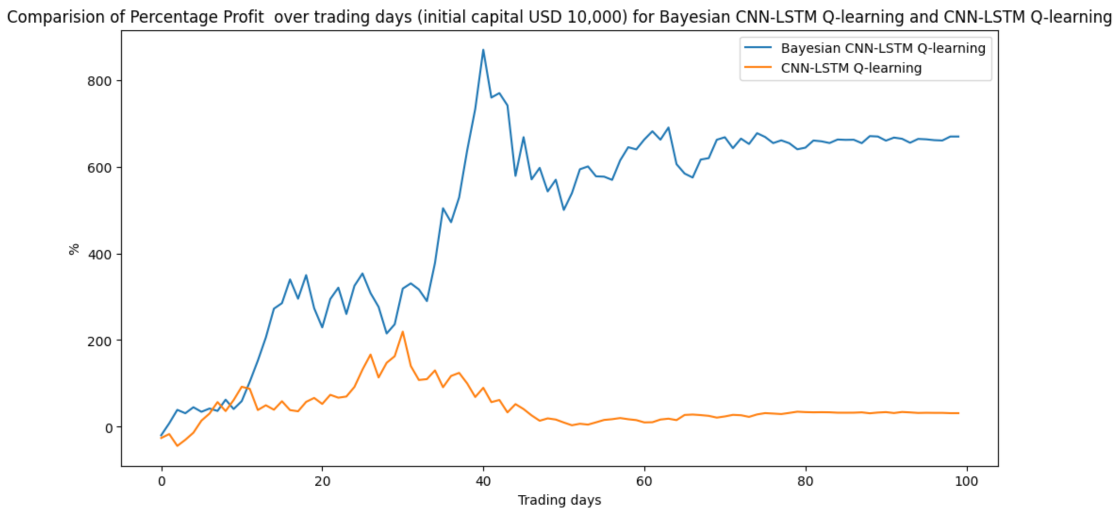
[275]:

```
plt.figure(figsize=(12, 6))
plt.plot(data_live_5['profit'], label="Bayesian CNN-LSTM Q-learning")
plt.plot(data_live_5['profit_cnn_lstm'], label="CNN-LSTM Q-learning")
plt.xlabel('Trading days')
plt.ylabel('USD')
plt.title(
    'Comparision of Profit over trading days (initial capital USD 10,000) for␣
 ↪Bayesian CNN-LSTM Q-learning and CNN-LSTM Q-learning'
 )
plt.legend()
plt.show()
```

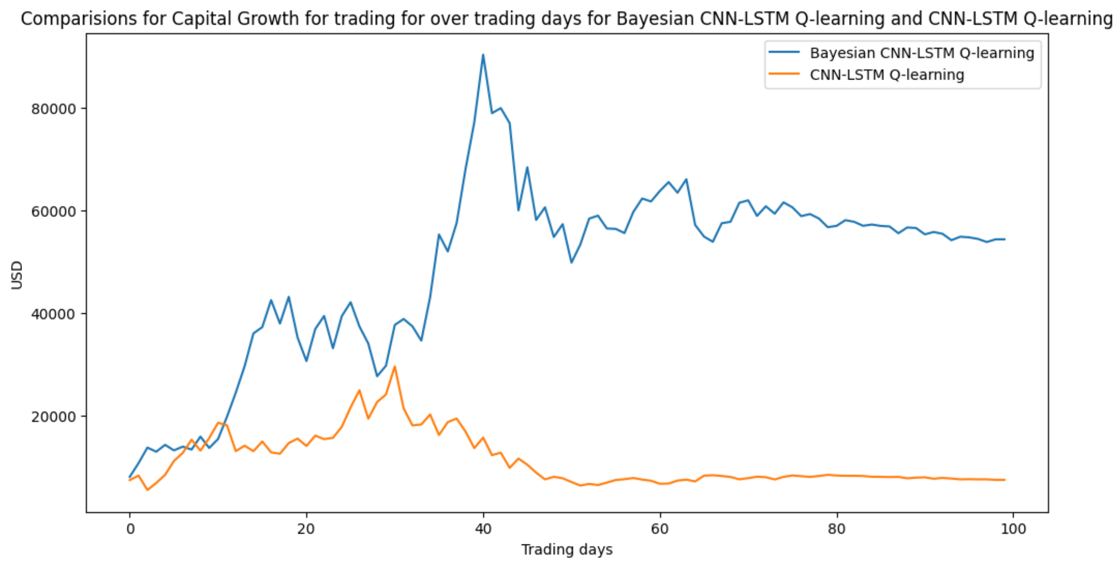


[276]:

```
plt.figure(figsize=(12, 6))
plt.plot(
    data_live_5['percentage_profit'],
    label="Bayesian CNN-LSTM Q-learning"
)
plt.plot(
    data_live_5['percentage_profit_cnn_lstm'],
    label="CNN-LSTM Q-learning"
)
plt.xlabel('Trading days')
plt.ylabel('%')
plt.title(
    'Comparision of Percentage Profit  over trading days (initial capital USD␣
 ↪10,000) for Bayesian CNN-LSTM Q-learning and CNN-LSTM Q-learning'
    )
plt.legend()
plt.show()
```



[277]:
```
plt.figure(figsize=(12, 6))
plt.plot(
    data_live_5['capital'],
    label='Bayesian CNN-LSTM Q-learning'
)
plt.plot(
    data_live_5['capital_cnn_lstm'],
    label='CNN-LSTM Q-learning'
)
plt.xlabel('Trading days')
plt.ylabel('USD')
plt.title(
    'Comparisions for Capital Growth for trading for over trading days for␣
 ↪Bayesian CNN-LSTM Q-learning and CNN-LSTM Q-learning'
)
plt.legend()
plt.show()
```



8 7. Marketing Timing using Bayesian CNN Q-learning

Now let's build a bayesian CNN deep Q-learning. The idea is to test how the q-learning agent will perform if the primary model is not a hybrid of CNN and LSTM, but still have the uncertainty of it's predictions estimated and fed to the agent.

[157]:
```
# For creating model and training
model_bay_cnn = Sequential()

# Creating the Neural Network model here...
# CNN layers
model_bay_cnn.add(
    TimeDistributed(
        Conv1D(64, kernel_size=3, activation='relu', input_shape=(None, 1,100,␣
 ↪1)
            )
    )
)
model_bay_cnn.add(
    TimeDistributed(
        Dropout(0.25)
    )
)
model_bay_cnn.add(
    TimeDistributed(
        MaxPooling1D(2)
    )
)
```

```python
model_bay_cnn.add(
    TimeDistributed(
        Conv1D(128, kernel_size=3, activation='relu')
    )
)
model_bay_cnn.add(
    TimeDistributed(
        MaxPooling1D(2)
    )
)
model_bay_cnn.add(
    TimeDistributed(
        Conv1D(64, kernel_size=3, activation='relu')
    )
)

model_bay_cnn.add(TimeDistributed(MaxPooling1D(2)))
model_bay_cnn.add(TimeDistributed(Flatten()))
#Final layers
model_bay_cnn.add(Dense(1, activation='linear'))
model_bay_cnn.compile(optimizer='adam', loss='mse', metrics=['mse', 'mae'])
```

Enable dropout during inference

[158]:
```python
def enable_dropout_bay_cnn(model_bay_cnn):
    for layer in model_bay_cnn.layers:
        if isinstance(layer, (Dropout, TimeDistributed)):
            layer.training = True
```

Train the Bayesian CNN model

[159]:
```python
# # Train the model

history_bay_cnn = model_bay_cnn.fit(
    X_train, y_train,
    batch_size=32,
    epochs=20,
    validation_data=(X_val, y_val),
    verbose=0
)
```

[152]:
```python
X_test.shape
```

[152]:
```
(634, 1, 100, 1)
```

Make multiple predictions

[165]:
```python
num_predictions_bay_cnn = 100
predictions_bay_cnn = []
```

```
for _ in range(num_predictions_bay_cnn):
    enable_dropout_bay_cnn(model_bay_cnn)
    pred = model_bay_cnn.predict(X_test,verbose=0)  # x_test is your test data
    # print(pred.shape)
    # print("predicted")
    predictions_bay_cnn.append(pred)

predictions_bay_cnn = np.array(predictions_bay_cnn)
```

[ ]:

Aggregate the predictions

[166]:
```
mean_prediction_bay_cnn = np.mean(predictions_bay_cnn, axis=0)
uncertainty_bay_cnn = np.var(predictions_bay_cnn, axis=0)
```

[167]:
```
uncertainty_bay_cnn.shape
```

[167]: (634, 1, 1)

[168]:
```
# Reshape the uncertainty
uncertainty_bay_cnn=np.reshape(uncertainty_bay_cnn,[uncertainty_bay_cnn.
 ↪shape[0],1])
```

[169]:
```
uncertainty_bay_cnn.shape
```

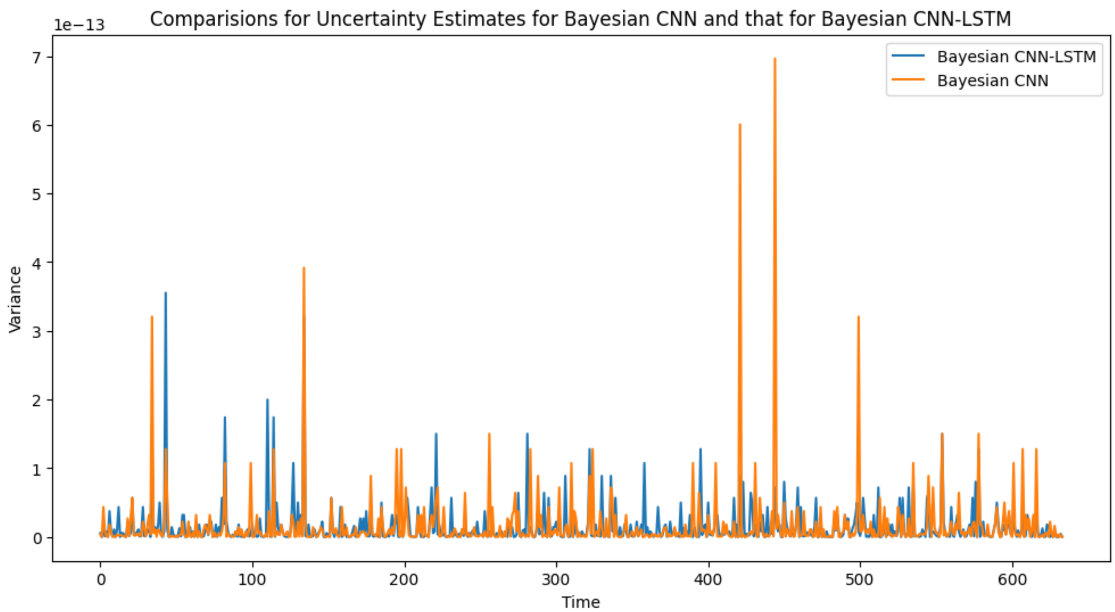
[169]: (634, 1)

[170]:
```
# From the trained Bayesian CNN-LSTM
num_predictions = 100
predictions = []

for _ in range(num_predictions):
    enable_dropout(loaded_bay_cnn_lstm_model)
    pred = loaded_bay_cnn_lstm_model.predict(X_test,verbose=0)  # x_test is␣
 ↪your test data
    # print(pred.shape)
    # break
    predictions.append(pred)

predictions = np.array(predictions)
mean_prediction = np.mean(predictions, axis=0)
uncertainty = np.var(predictions, axis=0)
```

[171]:
```
uncertainty.shape
```

[171]: (634, 1)

[172]:
```
# uncertainty
plt.figure(figsize=(12, 6))
plt.plot(uncertainty, label='Bayesian CNN-LSTM')
plt.plot(uncertainty_bay_cnn, label='Bayesian CNN')
plt.xlabel('Time')
plt.ylabel('Variance')
plt.title('Comparisions for Uncertainty Estimates for Bayesian CNN and that for␣
↪Bayesian CNN-LSTM')
plt.legend()
plt.show()
```



Save Bayesian CNN model

[173]:
```
# Save the model architecture as JSON
model_bay_cnn_json = model_bay_cnn.to_json()
with open("model_architecture_bay_cnn.json", "w") as json_file:
    json_file.write(model_bay_cnn_json)

# Save the model weights
model_bay_cnn.save_weights("trained_weights_bay_cnn.h5")

# Optionally, saving the entire model (including architecture and weights) in a␣
↪single .h5 file
model_bay_cnn.save("complete_bayesian_cnn.h5")
```

[174]:
```
# # Evaluate the model on the validation and test sets
val_loss_bay_cnn = model_bay_cnn.evaluate(X_val, y_val)
```

```
test_loss_bay_cnn = model_bay_cnn.evaluate(X_test, y_test)
print("Validation loss:", val_loss_bay_cnn)
print("Test loss:", test_loss_bay_cnn)

# Make predictions
y_pred_bay_cnn = model_bay_cnn.predict(X_test)
```

```
16/16 [==============================] - 0s 13ms/step - loss: 0.0045 - mse:
0.0045 - mae: 0.0520
20/20 [==============================] - 0s 10ms/step - loss: 0.0043 - mse:
0.0043 - mae: 0.0504
Validation loss: [0.004533048719167709, 0.004533048719167709,
0.05195485800504684]
Test loss: [0.004349007271230221, 0.004349007271230221, 0.05035331845283508]
20/20 [==============================] - 0s 14ms/step
```

[180]:
```
y_pred_bay_cnn.shape
```

[180]:
```
(634, 1, 1)
```

[186]:
```
y_pred_bay_cnn=np.reshape(y_pred_bay_cnn,[y_pred_bay_cnn.shape[0],1])
```

[187]:
```
data2["pred_bayesian_cnn"]=y_pred_bay_cnn
```

[188]:
```
data2
```

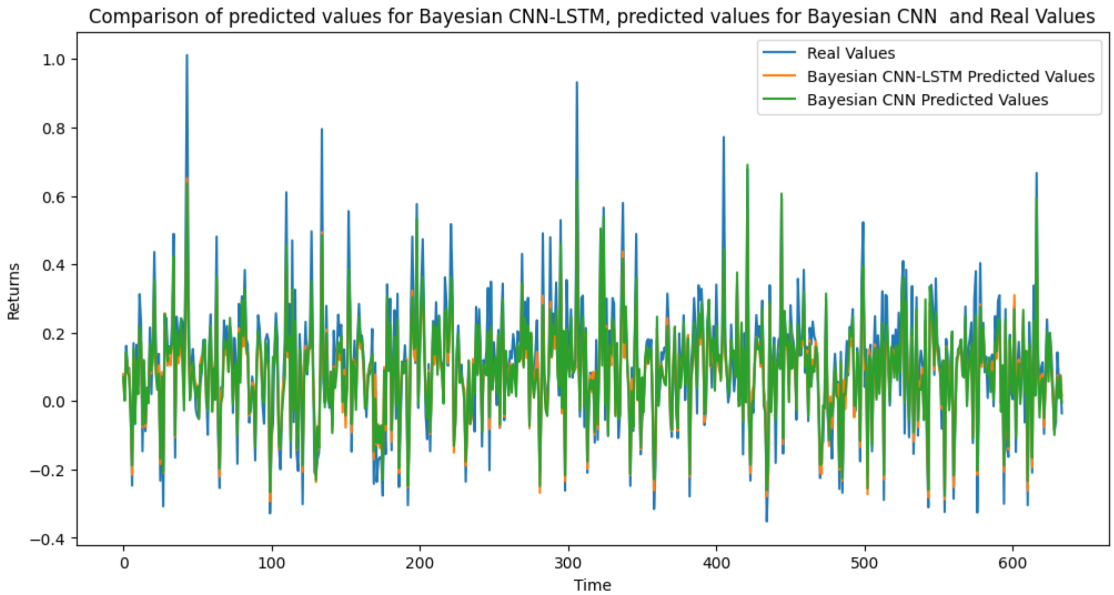
[188]:

	pred	real	pred_bayesian_cnn
0	0.078436	[[0.07325274729238496]]	0.069120
1	0.004642	[[0.03842559461456542]]	0.000967
2	0.132274	[[0.16137264609921742]]	0.144411
3	0.096807	[[0.09615067199751381]]	0.084266
4	0.087289	[[0.09673097399040065]]	0.072801
..	…	…	…
629	0.010501	[[-0.06192146481929599]]	-0.004028
630	0.075490	[[0.14251778602580817]]	0.069729
631	0.031253	[[0.05668098780701301]]	0.008192
632	0.075320	[[0.07631655504664701]]	0.072920
633	0.015449	[[-0.03594478131967395]]	-0.003971

[634 rows x 3 columns]

[191]:
```
plt.figure(figsize=(12, 6))
plt.plot(data2['real'], label='Real Values')
plt.plot(data2['pred'], label='Bayesian CNN-LSTM Predicted Values')
plt.plot(data2['pred_bayesian_cnn'], label='Bayesian CNN Predicted Values')
plt.xlabel('Time')
plt.ylabel('Returns')
```

```
plt.title('Comparison of predicted values for Bayesian CNN-LSTM, predicted␣
↪values for Bayesian CNN  and Real Values')
plt.legend()
plt.show()
```



Market timing with the Bayesian CNN Q-learning agent

[192]:
```
# Function to get states from your Bayesian CNN model and incorporate␣
↪uncertainty
def get_states_bay_cnn():
    # create an extended state that incorporated uncertainty estimation
    # and the predictions
    # We limit the state size to 100*2
    # This is necessary to maintain consistency
    extended_state = np.concatenate((y_pred_bay_cnn[:100,:],␣
↪uncertainty_bay_cnn[:100,:]), axis=1)
    return extended_state
```

[193]:
```
# The DQN agent
class DQNAgentBayesianCNN:
    def __init__(self, state_size, action_size,uncertainty_penalty):
        self.state_size = state_size
        self.action_size = action_size
        self.memory = deque(maxlen=200)  # Experience replay buffer
        self.gamma = 0.95  # Discount factor
        self.epsilon = 1.0  # Exploration-exploitation trade-off
        self.epsilon_decay = 0.995
```

```
        self.epsilon_min = 0.01
        self.learning_rate = 0.001
        self.uncertainty_penalty=uncertainty_penalty
        self.model = self._build_model()

    def _huber_loss(self,y_true, y_pred, clip_delta=1.0):
        error = y_true - y_pred
        cond  = keras_b.abs(error) <= clip_delta

        squared_loss = 0.5 * keras_b.square(error)
        quadratic_loss = (
                    0.5 * keras_b.square(clip_delta) +
                    clip_delta * (keras_b.abs(error) - clip_delta)
                )

        return keras_b.mean(tf.where(cond, squared_loss, quadratic_loss))

    def _build_model(self):
        model = Sequential()
        model.add(Flatten(input_shape=(state_size, 2)))  # Flatten layer to␣
↪reshape input
        model.add(Dense(24, activation='relu'))
        model.add(Dense(24, activation='relu'))
        model.add(Dense(self.action_size, activation='linear'))
        model.compile(
            loss=self._huber_loss,
            optimizer=Adam(learning_rate=self.learning_rate)
        )
        # model = Sequential()
        # model.add(Dense(24, activation='relu'))
        # model.add(Dense(24, activation='relu'))
        # model.add(Dense(self.action_size, activation='linear'))
        # model.compile(loss='mse', optimizer=Adam(learning_rate=self.
↪learning_rate))
        return model

    def remember(self, state, action, reward, next_state, done):
        # print(state.shape)
        self.memory.append((state, action, reward, next_state, done))

    def act(self, state,current_holding=0):
        if np.random.rand() <= self.epsilon:
            # Randomly select action from the action space: short, do nothing,␣
↪long
            return np.random.uniform(-1, 1)
        else:
            # Use the Q-network to select action based on state
```

```
            return np.argmax(self.model.predict(state,verbose=0)[0])

    def replay(self, batch_size):
        minibatch = random.sample(self.memory, batch_size)
        for state, action, reward, next_state, done in minibatch:
            target = reward
            # print(next_state.shape)
            if not done:
                # print(self.model.predict(next_state))
                target = reward + self.gamma * np.amax(self.model.
↪predict(next_state,verbose=0)[0])
            # print(state.shape)
            target_f = self.model.predict(state,verbose=0)
            # print(action)
            target_f[0][0] = target
            self.model.fit(state, target_f, epochs=1, verbose=0)
        if self.epsilon > self.epsilon_min:
            self.epsilon *= self.epsilon_decay

# The Market environment
class MarketEnvironmentBayesianCNN:
    def __init__(self,agent, max_episode_length=100, min_available_capital=10,␣
↪max_trades=None, profit_target=None, stop_loss=-5000):
        self.state_size = state_size  # The actual size of your state
        self.action_size = 1  # Example: Buy, Sell, Hold
        self.initial_capital = 10000  # Initial available capital
        self.transaction_cost = 0.01  # Transaction charge (1%)
        self.current_capital = self.initial_capital
        self.max_episode_length = max_episode_length
        self.min_available_capital = min_available_capital
        self.max_trades = max_trades
        self.profit_target = profit_target
        self.stop_loss = stop_loss
        self.num_trades = 0
        self.total_reward = 0
        self.uncertainty_penalty=agent.uncertainty_penalty

    def reset(self):
        # Reset logic
        self.current_capital = self.initial_capital
        self.num_trades = 0
        self.total_reward = 0
        # print(self.state_size)
        return np.random.rand(self.state_size)

    def step(self, action,time_state):
        # Extract market returns and uncertainty from the state
```

```
        market_returns = time_state[0]  # First column contains predicted␣
↪market returns
        uncertainty = time_state[1]     # Second column contains uncertainty␣
↪estimations
        # Simulated step function, returns next_state, reward, done
        next_state = np.random.rand(self.state_size,2)

        # Calculate bet size based on the selected action
        bet_size = abs(action) * self.current_capital

        # Calculate transaction cost based on the bet size
        total_transaction_cost=self.transaction_cost * bet_size
        # Subtract the transaction cost
        self.current_capital -= total_transaction_cost
        # Calculate the return based on the market return and the direction of␣
↪the trade
        # For a long position, return is market return * bet size
        # For not taking any position, return is 0
        if action > 0:
            return_direction = 1
        elif action<0:
            return_direction = -1
        else:
            return_direction = 0
        return_amount = return_direction * market_returns * bet_size
        yield_size=return_amount+bet_size
        if action > 0:
            # Adjust available capital based on bet size
            self.current_capital += return_amount

        # If action == 0, it means the agent wants to close the position
        elif action == 0:
            # Adjust available capital based on the current holding
            self.current_capital += return_amount
        # Calculate reward based on market return, transaction charges, and␣
↪uncertainty
        reward = return_amount
        #Since the uncertainty is calculated from return predictions,
        # The corresponding estimates take lower scales .i.e 1e-13
        # We have to scale this so that it can have effect on the reward
        # We scale by multiplying the uncertainty by 1e-11
        reward -= self.uncertainty_penalty * uncertainty*return_amount*1e-11
        # Increment total reward
        self.total_reward += reward

        # Increment number of trades
        self.num_trades += 1
```

```
        # Check termination conditions
        done = False
        if self.num_trades >= self.max_episode_length:
            done = True
        elif self.current_capital <= self.min_available_capital:
            done = True
        elif self.max_trades is not None and self.num_trades >= self.max_trades:
            done = True
        elif self.profit_target is not None and self.total_reward >= self.
 ↪profit_target:
            done = True
        elif self.stop_loss is not None and self.total_reward <= self.stop_loss:
            done = True
        return next_state, reward, done
```

[194]:
```
# Hyperparameters
states=get_states_bay_cnn()
state_size = states.size # The actual size of your state
print(state_size)
state_size=int(state_size/2) #The halfed state size for the input size
print(state_size)
action_size = 1  # Percentage defined as a ratio
batch_size = 32
# # market return

# Create the environment and agent
agent_bayesian_cnn = DQNAgentBayesianCNN(state_size, action_size,␣
 ↪UNCERTAINTY_PENALTY)
env_bayesian_cnn = MarketEnvironmentBayesianCNN(agent_bayesian_cnn)



# Training the DQN agent
for episode in range(EPISODES):  # Replace with the desired number of episodes
    state = env_bayesian_cnn.reset()
    state_from_cnn = get_states_bay_cnn()
    # state=state_from_lstm
    state = np.reshape(state_from_cnn, [1, state_size, 2])
    # print(state)
    total_episode_reward = 0  # Initialize total reward for the episode

    for time in range(EPISODE_LENGTH):  # Replace with the desired episode␣
 ↪length
        action = agent_bayesian_cnn.act(state)
        # print(market_returns_array[time])
        # Get this time state for reward calculation
        # print(state.shape)
```

```
        time_state=state[0][time]
        # print(time_state,time,episode)
        next_state, reward, done = env_bayesian_cnn.step(action,time_state)
        next_state = np.reshape(next_state, [1, state_size, 2])
        # print(state.shape)
        agent_bayesian_cnn.remember(state, action, reward, next_state, done)
        state = next_state
        total_episode_reward += reward  # Accumulate the reward obtained at␣
↪each time step
        if done:
            print("Episode: {}/{}, Reward score: {}".format(episode+1,␣
↪EPISODES, total_episode_reward))
            break
        # print(batch_size)
        if len(agent_bayesian_cnn.memory) > batch_size:
            agent_bayesian_cnn.replay(batch_size)
```

```
200
100
Episode: 1/40, Reward score: -7359.454289713845
Episode: 2/40, Reward score: -8252.83543120435
Episode: 3/40, Reward score: -25626.54677981978
Episode: 4/40, Reward score: -6745.918327585032
Episode: 5/40, Reward score: -6095.851209570532
Episode: 6/40, Reward score: -5504.140028830071
Episode: 7/40, Reward score: -9180.137751835859
Episode: 8/40, Reward score: -7627.4425355045305
Episode: 9/40, Reward score: -10035.047181861448
Episode: 10/40, Reward score: -22503.23998500572
Episode: 11/40, Reward score: -6171.367248093127
Episode: 13/40, Reward score: -21166.49567092733
Episode: 15/40, Reward score: -21718.03604126786
Episode: 16/40, Reward score: -7611.338167994795
Episode: 17/40, Reward score: -5634.821426713582
Episode: 18/40, Reward score: -17909.18260294973
Episode: 21/40, Reward score: -6808.155419559274
Episode: 22/40, Reward score: -6814.848477951175
Episode: 26/40, Reward score: -21400.538856795818
Episode: 29/40, Reward score: -6062.483594196465
Episode: 30/40, Reward score: -8656.78242631274
Episode: 31/40, Reward score: -6938.1536561476205
Episode: 33/40, Reward score: -7946.750925211741
Episode: 39/40, Reward score: -6075.925320274228
```

Save the bayesian CNN Q-learning agent model

[195]:
```
# Save DQNAgent object weights
agent_bayesian_cnn.model.save_weights('trained_qql_weights_bayesian_cnn.h5')
```

```python
# Assuming your agent is called 'agent'


# Save the agent's configurations using pickle
agent_config_bayesian_cnn = {
    'state_size': agent_bayesian_cnn.state_size,
    'action_size': agent_bayesian_cnn.action_size,
    # Add any other relevant configurations of your agent here
}
print(agent_config_bayesian_cnn)
with open("trained_qql_agent_config_bayesian_cnn.pkl", "wb") as config_file:
    pickle.dump(agent_config_bayesian_cnn, config_file)
```

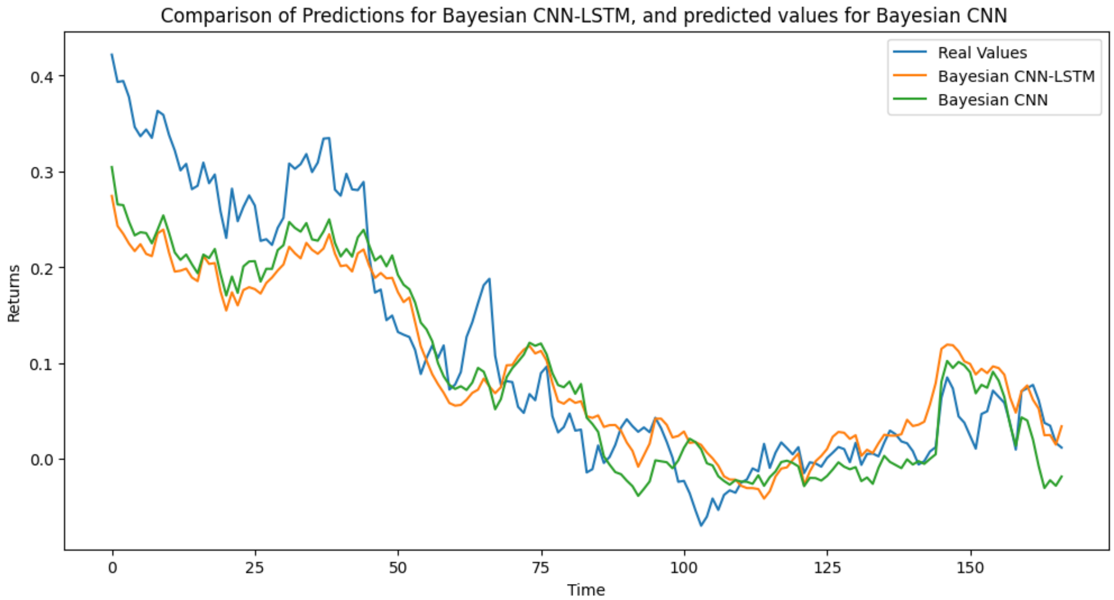
```
{'state_size': 100, 'action_size': 1}
```

Backtest Bayesian CNN Q-learning

[196]:
```python
# Load the saved model
loaded_model_bay_cnn = load_model('complete_bayesian_cnn.h5')
```

[197]:
```python
# Plot the graph comparing predicted values and real values
y_pred_live_bay_cnn = loaded_model_bay_cnn.predict(X_live)
pred_loss_bay_cnn = loaded_model_bay_cnn.evaluate(X_live, y_live)
# reshape to fit the model
y_pred_live_bay_cnn=np.reshape(y_pred_live_bay_cnn,[y_pred_live_bay_cnn.
 ↪shape[0],1])
print("Prediction loss:", pred_loss_bay_cnn)
data_live_2["pred_bay_cnn"]=y_pred_live_bay_cnn
plt.figure(figsize=(12, 6))
plt.plot(data_live_2['real'], label='Real Values')
plt.plot(data_live_2['pred'], label='Bayesian CNN-LSTM')
plt.plot(data_live_2['pred_bay_cnn'], label='Bayesian CNN')
plt.xlabel('Time')
plt.ylabel('Returns')
plt.title(
    'Comparison of Predictions for Bayesian CNN-LSTM, and predicted values for␣
 ↪Bayesian CNN '
)
plt.legend()
plt.show()
```

```
6/6 [==============================] - 1s 15ms/step
6/6 [==============================] - 1s 17ms/step - loss: 0.0031 - mse: 0.0031
- mae: 0.0451
Prediction loss: [0.003055047243833542, 0.003055047243833542,
0.04513537138700485]
```



Estimate the uncertainty of the predictions

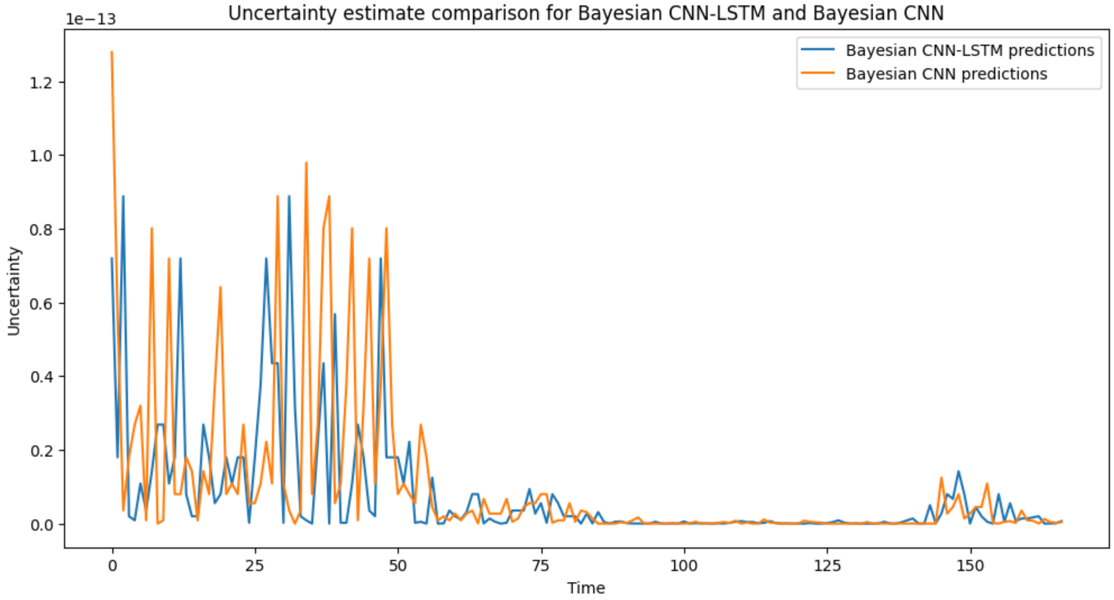
[198]:
```
num_predictions_live_bay_cnn = 100
predictions_live_bay_cnn = []

for _ in range(num_predictions_live_bay_cnn):
    enable_dropout_bay_cnn(loaded_model_bay_cnn)
    pred = loaded_model_bay_cnn.predict(X_live,verbose=0)
    predictions_live_bay_cnn.append(pred)

predictions_live_bay_cnn = np.array(predictions_live_bay_cnn)
```

[199]:
```
mean_prediction_live_bay_cnn = np.mean(predictions_live_bay_cnn, axis=0)
uncertainty_live_bay_cnn = np.var(predictions_live_bay_cnn, axis=0)
```

[200]:
```
# Reshape the uncertainty
uncertainty_live_bay_cnn=np.reshape(
    uncertainty_live_bay_cnn,
    [uncertainty_live_bay_cnn.shape[0],1]
)
```

[201]:
```
# uncertainty

plt.figure(figsize=(12, 6))
plt.plot(uncertainty_live, label='Bayesian CNN-LSTM predictions')
plt.plot(uncertainty_live_bay_cnn, label='Bayesian CNN predictions')
plt.xlabel('Time')
```

```
plt.ylabel('Uncertainty')
plt.title('Uncertainty estimate comparison for Bayesian CNN-LSTM and Bayesian␣
↪CNN')
plt.legend()
plt.show()
```



Loading Bayesian CNN Q-learning agent

[202]:
```
# Function to get states from your Bayesian CNN-LSTM model and incorporate␣
↪uncertainty
def get_states_live_bay_cnn():
    # create an extended state that incorporated uncertainty estimation
    # and the predictionsd
    extended_state = np.concatenate(
        (y_pred_live_bay_cnn[:100,:],
         uncertainty_live_bay_cnn[:100,:]),
        axis=1
    )
    return extended_state


# # Hyperparameters
states=get_states_live_bay_cnn()
state_size = states.size # The actual size of your state
state_size=int(state_size/2) #The halfed state size for the input size
print(state_size)
action_size = 1  # Percentage defined as a ratio
```

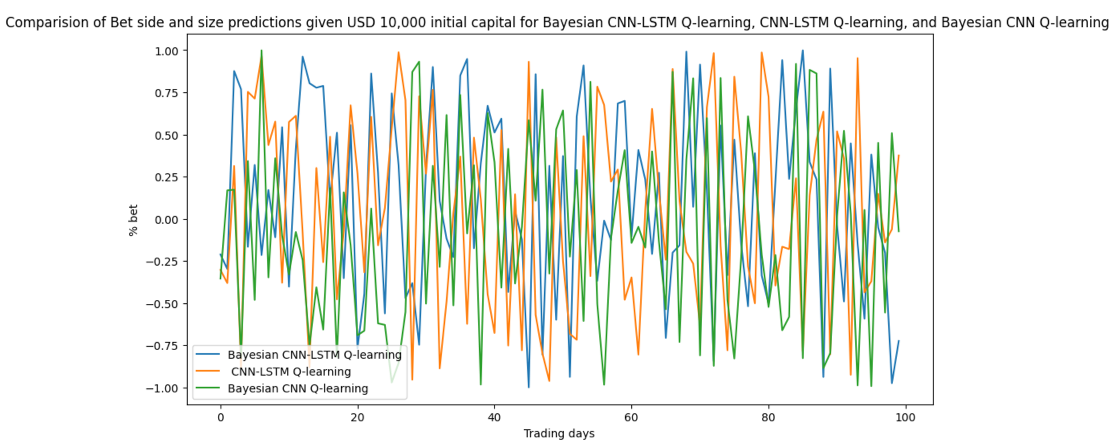
```
batch_size = 32
# market return
# Load trained model weights
loaded_dqq_agent_bay_cnn = DQNAgentBayesianCNN(
    state_size, action_size,UNCERTAINTY_PENALTY
)
loaded_dqq_agent_bay_cnn.model.load_weights('trained_qql_weights_bayesian_cnn.
↪h5')
```

100

Make Betsize predictions

[278]:
```
# Predict actions (sizes of bets)
actions_live_bay_cnn = []
for state in states:
    action = loaded_dqq_agent_bay_cnn.act(state)
    actions_live_bay_cnn.append(action)

# print("Predicted actions:", actions_live)
```

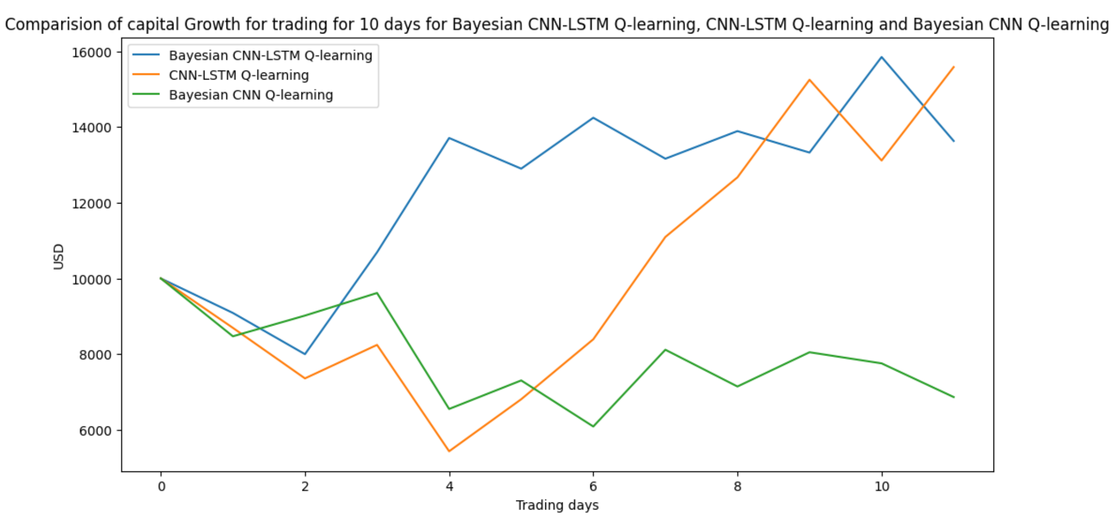
[279]:
```
plt.figure(figsize=(12, 6))
plt.plot(actions_live, label='Bayesian CNN-LSTM Q-learning')
plt.plot(actions_live_cnn_lstm, label=' CNN-LSTM Q-learning')
plt.plot(actions_live_bay_cnn, label='Bayesian CNN Q-learning')
plt.xlabel('Trading days')
plt.ylabel('% bet')
plt.title(
    'Comparision of Bet side and size predictions given USD 10,000 initial␣
↪capital for Bayesian CNN-LSTM Q-learning, CNN-LSTM Q-learning, and Bayesian␣
↪CNN Q-learning '
         )
plt.legend()
plt.show()
```



[280]:
```
cum_reward_bay_cnn=evaluate_actions(
    actions=actions_live_bay_cnn,
    market_returns=y_live,
    num_trades=10
)
```

[281]:
```
data_live_4['Capital_bayesian_cnn']=cum_reward_bay_cnn[4]
```

[282]:
```
plt.figure(figsize=(12, 6))
plt.plot(data_live_4['Capital'], label='Bayesian CNN-LSTM Q-learning')
plt.plot(
    data_live_4['Capital_cnn_lstm'],
    label='CNN-LSTM Q-learning'
)
plt.plot(
    data_live_4['Capital_bayesian_cnn'],
    label='Bayesian CNN Q-learning'
)
plt.xlabel('Trading days')
plt.ylabel('USD')
plt.title(
    'Comparision of capital Growth for trading for 10 days for Bayesian␣
↪CNN-LSTM Q-learning, CNN-LSTM Q-learning and Bayesian CNN Q-learning'
)
plt.legend()
plt.show()
```



Profit comparisions

[283]:
```python
# Bayesian CNN-LSTM Q-learning
print(
    f"Total profit = {cum_reward[0]}",
    f"%-profit = {cum_reward[1]}",
    f"Total trades = {cum_reward[2]}"
    )
```

```
Total profit = 4100.65129072707 %-profit = 41.0065129072707 Total trades = 10
```

[284]:
```python
# CNN-LSTM Q-learning
print(
    f"Total profit = {cum_reward_cnn_lstm[0]}",
    f"%-profit = {cum_reward_cnn_lstm[1]}",
    f"Total trades = {cum_reward_cnn_lstm[2]}"
    )
```

```
Total profit = 6169.304903650239 %-profit = 61.69304903650239 Total trades = 10
```

[285]:
```python
# Bayesian CNN Q-learning
print(
    f"Total profit = {cum_reward_bay_cnn[0]}",
    f"%-profit = {cum_reward_bay_cnn[1]}",
    f"Total trades = {cum_reward_bay_cnn[2]}"
    )
```

```
Total profit = -2785.707138620319 %-profit = -27.857071386203184 Total trades =
10
```

Agents performance based on the number of trades

[286]:
```python
num_trades_profits_bay_cnn=[]
num_trades_percentage_profits_bay_cnn=[]
num_trades_cum_reward_bay_cnn=[]
for i in range(1,101):
    cum_reward_=evaluate_actions(
        actions=actions_live_bay_cnn,
        market_returns=y_live,
        num_trades=i
    )
    num_trades_profits_bay_cnn.append(cum_reward_[0])
    num_trades_percentage_profits_bay_cnn.append(cum_reward_[1])
    #Get the cummulative capital on the last trading day
    num_trades_cum_reward_bay_cnn.append(cum_reward_[4][-1])
```

[287]:
```python
trade_databay_cnn={
    "profit_bay_cnn":num_trades_profits_bay_cnn,
    "percentage_profit_bay_cnn":num_trades_percentage_profits_bay_cnn,
    "capital_bay_cnn":num_trades_cum_reward_bay_cnn
}
```

```
data_live_5['profit_bay_cnn']=num_trades_profits_bay_cnn
data_live_5['percentage_profit_bay_cnn']=num_trades_percentage_profits_bay_cnn
data_live_5['capital_bay_cnn']=num_trades_cum_reward_bay_cnn
```

Statistical summaries of the trade

[288]:
```
data_live_5.describe()
```

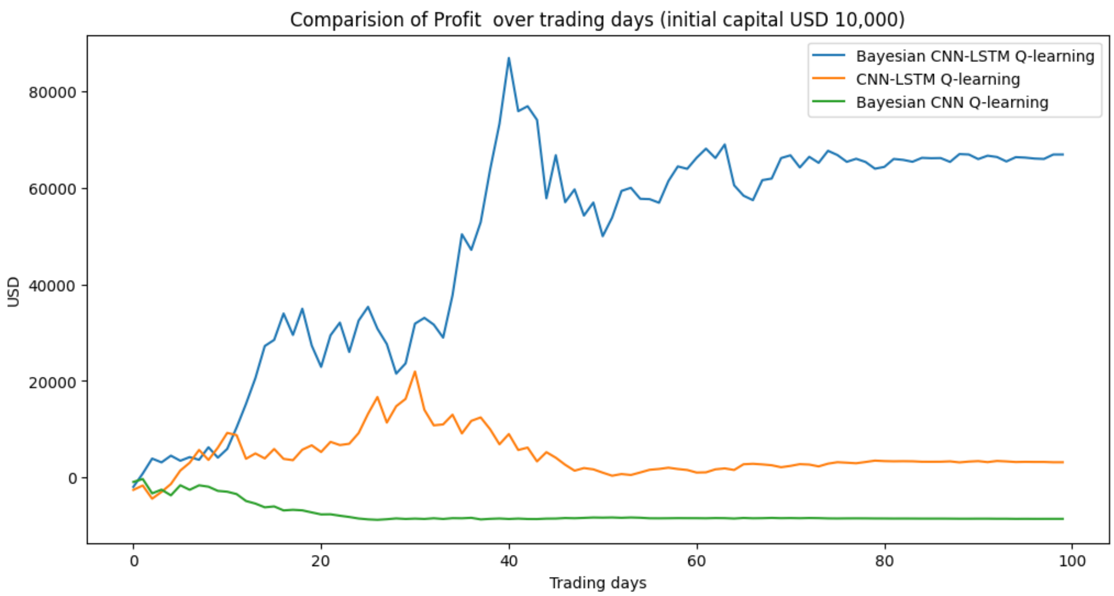
[288]:

	profit	percentage_profit	capital	profit_cnn_lstm
count	100.000000	100.000000	100.000000	100.000000
mean	48667.380755	486.673808	48741.286118	4597.352553
std	22806.859535	228.068595	17488.590802	4371.249350
min	-1954.138739	-19.541387	7997.720271	-4409.414467
25%	30497.879862	304.978799	37347.147885	2245.490590
50%	59533.747939	595.337479	55364.160782	3253.270459
75%	66163.825686	661.638257	58871.838426	5963.971613
max	86931.182176	869.311822	90367.524775	21950.973871

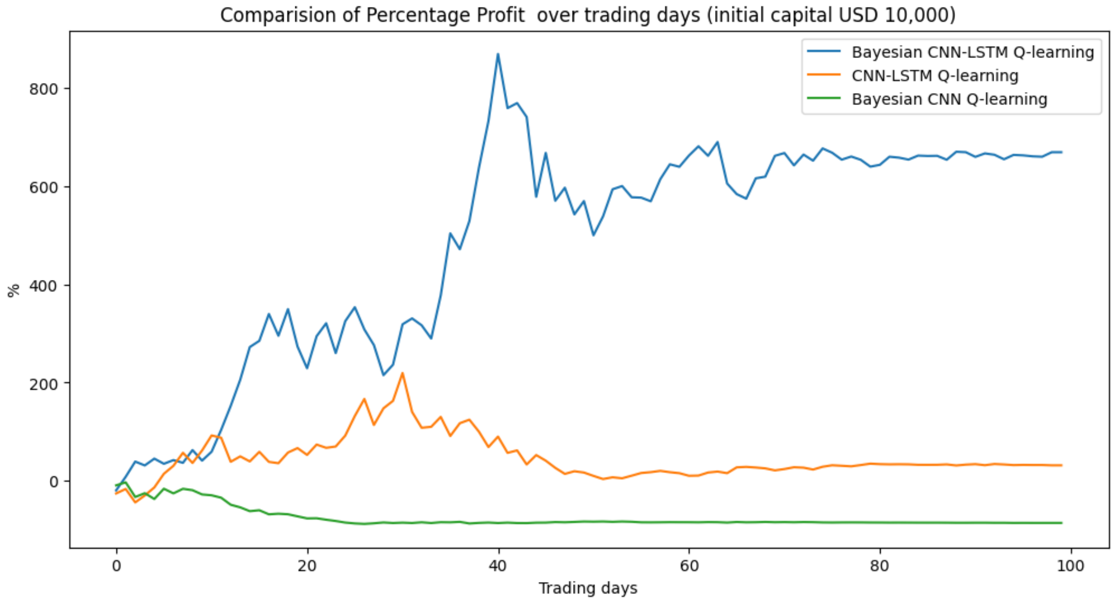
	percentage_profit_cnn_lstm	capital_cnn_lstm	profit_bay_cnn
count	100.000000	100.000000	100.000000
mean	45.973526	11207.960032	-7552.493166
std	43.712494	5096.115758	2080.994995
min	-44.094145	5431.670748	-8783.417207
25%	22.454906	7538.698475	-8532.679500
50%	32.532705	8202.446402	-8459.567501
75%	59.639716	14670.491519	-8298.073313
max	219.509739	29552.931223	-319.813699

	percentage_profit_bay_cnn	capital_bay_cnn
count	100.000000	100.000000
mean	-75.524932	1803.023453
std	20.809950	2247.775487
min	-87.834172	546.401331
25%	-85.326795	719.887706
50%	-84.595675	824.281048
75%	-82.980733	1018.129825
max	-3.198137	9614.943956

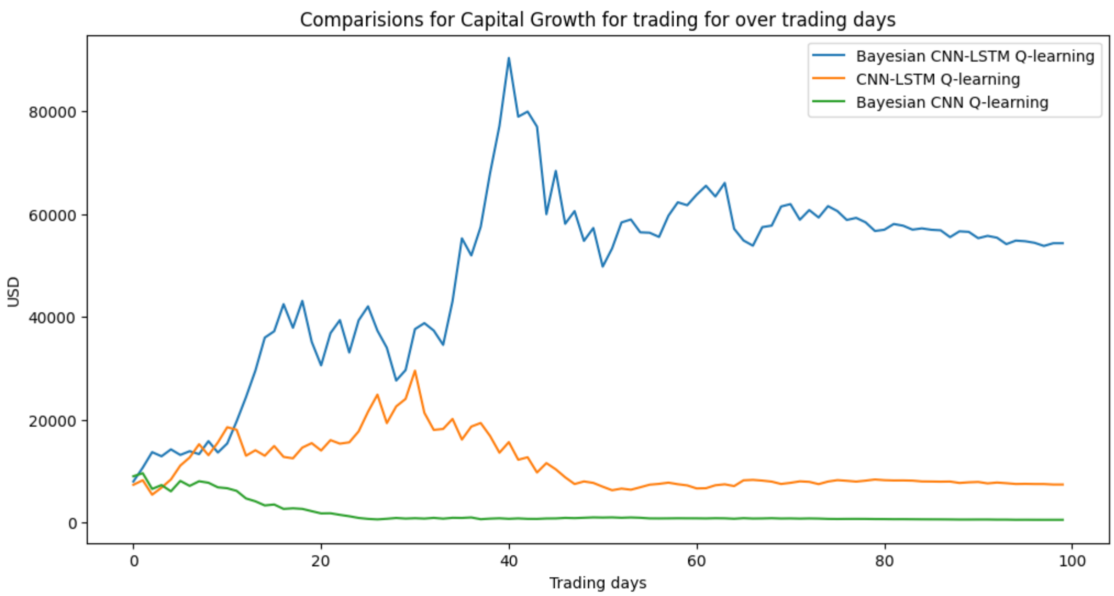
[289]:
```
plt.figure(figsize=(12, 6))
plt.plot(data_live_5['profit'], label="Bayesian CNN-LSTM Q-learning")
plt.plot(data_live_5['profit_cnn_lstm'], label="CNN-LSTM Q-learning")
plt.plot(data_live_5['profit_bay_cnn'], label="Bayesian CNN Q-learning")
plt.xlabel('Trading days')
plt.ylabel('USD')
plt.title('Comparision of Profit  over trading days (initial capital USD␣
↪10,000)')
plt.legend()
plt.show()
```



[290]:
```python
plt.figure(figsize=(12, 6))
plt.plot(
    data_live_5['percentage_profit'],
    label="Bayesian CNN-LSTM Q-learning"
)
plt.plot(
    data_live_5['percentage_profit_cnn_lstm'],
    label="CNN-LSTM Q-learning"
)
plt.plot(
    data_live_5['percentage_profit_bay_cnn'],
    label="Bayesian CNN Q-learning"
)
plt.xlabel('Trading days')
plt.ylabel('%')
plt.title('Comparision of Percentage Profit  over trading days (initial capital␣
 ↪USD 10,000)')
plt.legend()
plt.show()
```



[291]:
```
plt.figure(figsize=(12, 6))
plt.plot(
    data_live_5['capital'],
    label='Bayesian CNN-LSTM Q-learning'
)
plt.plot(
    data_live_5['capital_cnn_lstm'],
    label='CNN-LSTM Q-learning'
)
plt.plot(
    data_live_5['capital_bay_cnn'],
    label='Bayesian CNN Q-learning'
)
plt.xlabel('Trading days')
plt.ylabel('USD')
plt.title('Comparisions for Capital Growth for trading for over trading days')
plt.legend()
plt.show()
```


Comparisions for Capital Growth for trading for over trading days
Bayesian CNN-LSTM Q-learning
CNN-LSTM Q-learning
Bayesian CNN Q-learning
USD
80000
60000
40000
20000
0
0
20
40
60
80
100
Trading days

[ ]: