sequences derived from tokenization were then padded to a uniform length of 100.

The dataset was split into training and validation sets, using an 80-20 split ratio. The random state for the split was set to 42 to ensure repeatability.

8) Model Architecture: The neural network model for this research is constructed using the sequential API from TensorFlow's Keras. The architecture consists of:

- An embedding layer with an input vocabulary size equal to the number of unique words in the dataset plus one (to account for the out-of-vocabulary token), and an embedding dimension of 100.
- A flattened layer to transform the embedded sequences into a 1D array.
- A dense layer with 10 neurons and a ReLU activation function, is further enhanced with L2 regularization.
- A dropout layer with a drop rate of 50% to mitigate overfitting.
- An output dense layer with one neuron and a sigmoid activation function, tailored for binary classification tasks.

The model was compiled with the Adam optimizer, utilizing the binary cross-entropy loss function. Accuracy was designated as the primary evaluation metric.

its output are detailed below:

13) Output and Evaluation: **Observations:** As presented in Table I, the model achieved an accuracy of approximately 96% on the validation set.

C. Model Architecture: Long Short-Term Memory Network

To address our text forensics challenge, we utilized a Long Short-Term Memory (LSTM) network, a recurrent neural network (RNN) variant renowned for its capability to remember long-term dependencies within sequential data. Our Twitter dataset, which underwent sequential preprocessing, aligns well with the capabilities of an LSTM network, making it an appropriate choice of architecture for our study.

1) Network Design: Our study's designed LSTM network consists of the following layers:

- **Embedding Layer**: Converts tokenized tweets into dense vectors with a fixed length, encapsulating the semantic essence of words. We set the embedding input dimension to 5000 and the output dimension to 128.
- **LSTM Layer**: With 128 units, this layer is capable of capturing sequential information and includes dropout and recurrent dropout options to mitigate overfitting, both set to 20%.